Developing spatial models of health service access and utilisation to define health equity in Kenya

Thesis

Link(s) to article on publisher's website:
http://dx.doi.org/doi:10.21954/ou.ro.0000e946

UNRESTRICTED

Developing spatial models of health service access and utilisation to define health equity in Kenya

By

Abdisalan Mohamed Noor, (B.Sc.),
University of Nairobi, Kenya.

Kenya Medical Research Institute/Wellcome Trust Research Programme, Nairobi, Kenya,

in collaboration with

The Department of Zoology, University of Oxford, United Kingdom.

Thesis submitted to the Open University, Faculty of Social Sciences, Geography, in partial fulfilment of the requirements for the degree of Doctor of Philosophy.

July 2005

AUTHOR NO W147326X
DATE OF SUBMISSION 22 MARCH 2005
DATE OF AWARD 19 JULY 2005

DEDICATION

To my mum (1954-2004), for her love

"……… ye be kind to thy parents. Whether one or both of them attain old age in thy life, say not to them a word of contempt, nor repel them, but address them in terms of honour. And out of kindness, lower to them the wing of humility, and say: 'My Lord, bestow on them Thy Mercy even as they cherished me in childhood" (Al-Qur'an, 17: 23-24).

ACKNOWLEDGEMENTS

This thesis is the result of the encouragement, support and advice of many people. I owe a lot to my director of studies, Professor Bob Snow without whom this work would have been impossible. I would like to thank him further for his patience, understanding and guidance in my many moments of naiveté. I hope I have learned well. I would like to thank my second supervisor, Dr. Simon Hay and his colleagues at the Department of Zoology, University of Oxford, particularly Dr. Andy Tatem and Dr. Carlos Guerra, for their efforts in ensuring that I had all I needed to do my work and for the constant guidance. I would also like to thank the Wellcome Trust (UK) for funding my thesis. My special thanks also go to Dr. Hay and his wife, Sarah, for being such kind hosts during my stay in Oxford.

My profound gratitude goes to Prof. Peter Atkinson and Pete Gething of the University of Southampton, who have helped me with development of the spatial models. Special mention goes to Pete Gething for the many late hours spent helping me with the various algorithms and for letting me stay at his house during my time in Southampton. I acknowledge the help of my colleagues Abdinasir Amin and Dejan Zurovac in refining the community and health facility survey data respectively. I would also like to thank Priscilla Gikandi for her extensive help with the health service database. I would like to acknowledge the Central Bureau of Statistics for helping me with the population census and administrative data, the Kenya Wildlife Service, especially Mr. Wycliffe Mutero, for his help with the maps of national parks, game reserves and sanctuaries. I would like to thank Mr. Russell Kruska of the International Livestock Research Institute for his help with the elevation data. I am grateful to Mr. Michael Hansen of Danish International Development Agency and Dr. Henri van der Homberg of the German Technical Cooperation for providing health service data for their respective programme districts.

I acknowledge the many field workers and members of the provincial and district health management teams who have tirelessly helped me in developing the necessary data for the thesis and for their prompt response whenever queries were raised. I am grateful to Lydiah Mwangi and Lucy Muhunyo for data entry. Finally, I thank my friends and family, and in particular my father, for helping me maintain focus in writing the thesis when faced with the inevitable, but nonetheless daunting difficulties of life.

ABSTRACT

Background: Distance is important in access to health care, in turn a key measure of attainment of Millennium Development Goals. The aim of this thesis was to develop spatial models of access and utilisation of government health services in Kenya.

Methods: High-resolution spatial data on health services, population, transportation, elevation, rivers and gazetted areas have been developed for four study districts. Four theoretical spatial access and utilisation models, based on different distance definitions, were then developed for each district. The assumptions of commonly used access models were assessed using data from health facility-based surveys. High-resolution household data were used to adjust the models for actual use. A test of model-fit was carried out and the 'best-fit' model identified. The potential of scaling-up the best-fit model to the national-level was explored.

Results: Six kilometres was the threshold within which most patients used government health services for fever treatment. Higher-order facilities had larger patients draw. Adjusting the models for competition between facilities increased the mean distances to health services. The model incorporating the transport network and physical barriers to movement, adjusted for competition was found to be the 'best-fit' model. The Euclidean model estimated that 82% of the population in the districts lived within commonly used target of 5 km of government health services; 78% when adjusted for competition; while the best-fit model further reduced the estimate to 63%. The models could not be scaled-up to national level due to paucity of appropriate data at this level.

Conclusions: Adjustment of models for competition improves their predictive accuracies. The Euclidean model commonly used to measure access estimates 19% (6 million) more people nationwide than the best-fit model to have access to government health. This has

major implications for measurement of health development goals. To redress the situation, more research needs to be done in defining spatial access better by including all the key spatial and aspatial parameters. Ultimately, the use of the best access model at the national level requires the development of more and higher-resolution spatial and empirical data.

LIST OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDICES

LIST OF ABBREVIATIONS

CBH	Central Board of Health
CBS	Central Bureau of Statistics
CDF	Constituency Development Fund
CHAK	Christian Health Associations of Kenya
CI	Confidence Interval
CGIS	Canada Geographic Information Systems
CM	Central Meridian
CMH	Commission on Macroeconomics and Health
D	Dispensary
DANIDA	Danish International Development Agency
DC	District Commissioner
DCW	Digital Chart of the World
DD	Decimal Degrees
DDC	District Development Committee
DDPs	District Development Plans
DEM	Digital Elevation Model
DHMT	District Health Management Teams
DHMB	District Health Management Board
DMS	Degree-Minutes-Seconds
DOMC	Division of Malaria Control
DOTs	Directly Observed Treatment strategy
DP	Development Plan
DPHC	Division of Primary Health Care
DSA	Development Solutions Africa
DSS	Demographic Surveillance Systems
EA	Enumeration Area
EANMAT	East African Network for Monitoring Anti-malarial Treatment
EIP	Evidence and Information for Policy
ESRI	Environmental Systems Research Institute
ERSWEC	Economic Recovery Strategy for Wealth and Employment Creation
EPI	Expanded Programme on Immunisation
FCM	Floating Catchment Method
FGDC	Federal Geographic Data Committee
FPLM	Family Planning and Logistics Management
GEE	Generalised Estimating Equations
GIS	Geographical Information Systems
GoK	Government of Kenya
GP	General Practitioner
GPS	Global Positioning Systems
GPW	Gridded Population of the World
GTZ	German Technical Corporation
H	Hospital
HC	Health Centre
HIV/AIDS	Human Immunodeficiency Virus/Acquired Immune Deficiency Syndrome
HMIS	Health Management Information Systems
HPD	Human Population Distribution
HSRS	Health Sector Reform Strategy
IBEAC	Imperial British East African Company

ICFD	International Conference on Financing for Development
IDW	Inverse Distance Weighting
IDs	Identification Numbers
ILRI	International Livestock Research Institute
IMF	International Monetary Fund
ISEqH	International Society for Equity in Health
JERS-1	Japanese Earth Resources Satellite-1
JICA	Japanese International Co-operation Agency
KDHS	Kenya Demographic and Health Survey
KEMRI	Kenya Medical Research Institute
KEPI	Kenya Expanded Programme for Immunisation
KG	Kenya Gazette
KHPF	Kenya Health Policy Framework
KMD	Kenya Medical Directory
KNH	Kenyatta National Hospital
KNMS	Kenya National Malaria Strategy
Kshs	Kenya Shillings
KSPA	Kenya Service Provision Assessment
KWS	Kenya Wildlife Service
LA	Local Authority
MARA	Mapping Malaria Risk in Africa
MDGs	Millennium Development Goals
MIS	Malaria Information Systems
MLG	Ministry of Local Government
MMR	Maternal Mortality Ratio
MoH	Ministry of Health
MSH	Médecins Sans Frontiere
NCPD	National Council for Population Development
NGO	Non Governmental Organisation
NHIF	National Hospital Insurance Fund
NHSD	National Health Service Database
NHSSP	National Health Sector Strategic Plan
NSEC	National Economic Social Council
OA	Overall Accuracy
OSD	On-Screen Digitising
PAHO	Pan-American Health Organization
PHC	Primary Health Care
PHMB	Provincial Health Management Board
PHMT	Provincial Health Management Team
PMO	Provincial Medical Officer
PNG	Papua New Guinea
PRSPs	Poverty Reduction Strategy Papers
RIEAL	Research International East Africa Limited
RBM	Roll Back Malaria
RMSE	Root Mean Square Error
RUR	Relative Utilisation Rate
SA	Spatial Accessibility
SP	Sulphadoxine-Pyrimethamine
SSA	sub-Saharan Africa
SYMAP	Synagraphic Mapping System
TALA	Trypanosomiasis and Land-Use in Africa
TEHIP	Tanzania Essential Health Interventions Project
TM	Thematic Mapper

TP	Thiessen Polygon
WHO	World Health Organization
UN	United Nations
UNDP	United Nations Development Programme
UNFPA	United Nations Population Fund
UNICEF	United Nations Children Fund
UN-SALB	United Nations- Second Level Administrative Boundaries
UR	Utilisation Rate
USPHS	United States Public Health Service
UTM	Universal Transverse Mercator
WHO-PHMP	World Health Organisation- Public Health Mapping Project

CHAPTER 1:
Introduction and Literature Review

1.1 Background

The international development agenda is now driven largely by eight Millennium Development Goals (MDGs). The health MDGs relate to the reduction of the burden of HIV/AIDS, tuberculosis and malaria. Achieving these goals is dependent on access to effective and equitable health services. Geographic factors play an important role in access to and use of health services. Widely used descriptive measures of spatial access have rarely been systematically evaluated, however. In this thesis the determinants of access to and utilisation of health services in different settings were reviewed, with emphasis on the spatial factors. High-resolution spatial and epidemiological data on health services, population, transport network, topography, land cover and paediatric fever treatment were obtained for four study districts to develop access and utilisation models for government health services in Kenya. Community survey data were used to model actual utilisation of government health services by febrile children. A model based on the transport network and accounting for the effect of natural barriers on mobility was then implemented and adjusted for actual use patterns. The predictive accuracies of this refined model versus the commonly used Euclidean distance metrics were then assessed. The practicalities in scaling this spatial model to the national level, its limitations and the broader implications for assessing geographic access to health services are described.

This introductory chapter has eight sections. Section 1.2 reviews the international targets for global health, the main development goals and the role of health in poverty reduction. In Section 1.3, a brief description of the role and objectives of health systems is presented against the current state of health systems in low-income countries. Section 1.4 begins with a description of the role of health equity as a measure of the performance of a health system. The definitions, concepts, determinants and methods of measuring health equity are reviewed. Section 1.5 focuses on access and utilisation of health care as a measure of health equity with a detailed review of the determinants of access and use of health services with a special emphasis on distance in access and utilisation of health care. The methods of measuring spatial accessibility and their limitations are discussed in Section 1.6. A brief description of the history and evolution of spatial modelling is given in Section 1.7. In Section 1.8 the role of Geographical Information Systems (GIS) and their impact on spatial analytical methods is described. The history and applications of GIS in public health, globally and in sub-Saharan Africa (SSA) are discussed and factors limiting the realisation of the full potential of GIS in public health in SSA are outlined. Finally, Section 1.9 presents the purpose, and scope of the thesis, followed by a brief outline of the contents of subsequent chapters.

1.2 Global targets for health

1.2.1 Millennium Development Goals (MDGs)

On 17 December 1998, the United Nations (UN) General Assembly adopted resolution 53/202 by which it decided to convene the Millennium Summit of the UN. The summit was held at UN Headquarters in New York on the 6-8 September 2000 (www.un.org/millennium). One hundred and forty seven heads of state attended the summit and committed their nations to define and strengthen a set of global targets for peace, human rights, democracy, strong governance, environmental sustainability, poverty reduction, and to promote the principles of human dignity, equality and equity. The resulting UN Millennium Declaration was adopted by 189 of the 191 UN member states and was summarised as follows;

> '*We recognise that, in addition to our separate responsibilities to our individual societies, we have a responsibility to uphold the principles of human dignity, equality and equity at the global level. As leaders we have a duty therefore to all the world's people, especially the most vulnerable and, in particular, the children of the world, to whom the future belongs*' (UN, 2000).

At the summit it was recognised that simply adopting the declaration was insufficient. Instead, the world leaders committed themselves to a set of ambitious targets with clearly defined deadlines and indicators to monitor progress. The UN Secretary-General was asked to prepare a road map for achieving the Declaration's commitments resulting in the eight MDGs, with its 18 targets and 48 indicators (UN, 2001). These MDGs, targets and indicators are given in Table 1.1.

Of the 48 indicators, six are directly related to access to health services, water resources or markets for produce and international trade and aid. Three of the eight MDGs are health goals: a) reduction of child mortality, b) improvements of maternal health, and c) combating of HIV/AIDS, malaria and other diseases. Important to the attainment of the health MDGs is access to effective malaria preventive and treatment measures and access to directly observed treatment short course (DOTS) for tuberculosis (TB). As will be discussed in detail in Section 1.5.3, a fundamental factor driving access to these services is the distance between the population's place of residence and the location of these services.

Table 1.1 Millennium development goals, targets and indicators[1]

Goals and targets	Indicators
Goal 1. Eradicate extreme hunger and poverty	
Target 1. Halve, between 1990 and 2015, the proportion of people whose income is less than one dollar a day	1. Proportion of population below $1 per day 2. Poverty gap ratio (incidence x depth of poverty) 3. Share of poorest quintile in national consumption
Target 2. Halve, between 1990 and 2015, the proportion of people who suffer from hunger	4. Prevalence of underweight children (under five years of age) 5. Proportion of population below the minimum level of dietary energy consumption
Goal 2. Achieve universal primary education	
Target 3. Ensure that, by 2015, children everywhere, boys and girls alike, will be able to complete a full course of primary schooling	6. Net enrolment ratio in primary education 7. Proportion of pupils starting grade 1 who reach grade 5

[1] More details on the MDGs, targets and indicators are given in the UN document A/56/326, Road map towards the implementation of the UN Millennium Declaration, September 2001 (www.un.org/millennium).

	8. Literacy rate of 15-24-year-olds
Goal 3. Promote gender equality and empower women	
Target 4: Eliminate gender disparity in primary and secondary education, preferably by 2005, and to all levels no later 2015	9. Ratio of girls to boys in primary, secondary and tertiary education 10. Ratio of literate females to males of 15-to-24-year-olds 11. Share of women in wage employment in the non-agricultural sector 12. Proportion of seats held by women in national parliament
Goal 4. Reduce child mortality	
Target 5. Reduce by two thirds, between 1990 and 2015, the under-five mortality rate	13. Under-five mortality rate 14. Infant mortality rate 15. Proportion of 1-year-old children immunised against measles
Goal 5. Improve maternal health	
Target 6. Reduce by three quarters, between 1990 and 2015, the maternal mortality ratio	16. Maternal mortality ratio 17. Proportion of births attended by skilled health personnel
Goal 6. Combat HIV/AIDS, malaria and other diseases	
Target 7. Halt by 2015 and begin to reverse the spread of HIV/AIDS	18. HIV prevalence among 15-to-24-year-old pregnant women 19. Contraceptive prevalence rate 20. Number of children orphaned by HIV/AIDS
Target 8. Halt by 2015 and began to reverse the incidence of malaria, TB and other major diseases	21. Prevalence and death associated with malaria 22. Proportion of population in malaria risk areas using effective malaria prevention and treatment measures 23. Prevalence and death associated with tuberculosis 24. Proportion of tuberculosis cases detected and cured under directly observed treatment short course
Goal 7. Ensure environmental sustainability	
Target 9. Integrate the principles of sustainable development into country policies and programmes and reverse the loss of environmental resources	25. Proportion of land area covered by forests 26. Land area protected to maintain biological diversity 27. GDP per unit of energy use (as proxy for energy efficiency) 28. Carbon dioxide emissions (per capita) [Plus two figures of global atmospheric pollution: ozone depletion and the accumulation of global warming gases]
Target 10. Halve by 2015 the proportion of people without sustainable access to safe drinking water	29. Proportion of people with sustainable access to an improved water source
Target 11. By 2020 to have achieved a significant	30. Proportion of people with access to

improvement in the lives of at least 100 million slum dwellers	improved sanitation 31. Proportion of people with access to secure tenure
Goal 8. Develop a global partnership for development	
Targets 12-18. These deal with the establishment of non-discriminatory trading and financial systems, addressing the special needs of least developed countries (LDCs), landlocked countries and small islands, dealing comprehensively with debt problems, implementing strategies for decent and productive work for youth, providing access to affordable essential drugs to LDCs in collaboration with pharmaceutical companies, making benefits of new technologies available to LDCs in collaboration with the private sector.	Indicators 32-48. These are indicators which measure the broad fields of official development assistance, market access and debt sustainability

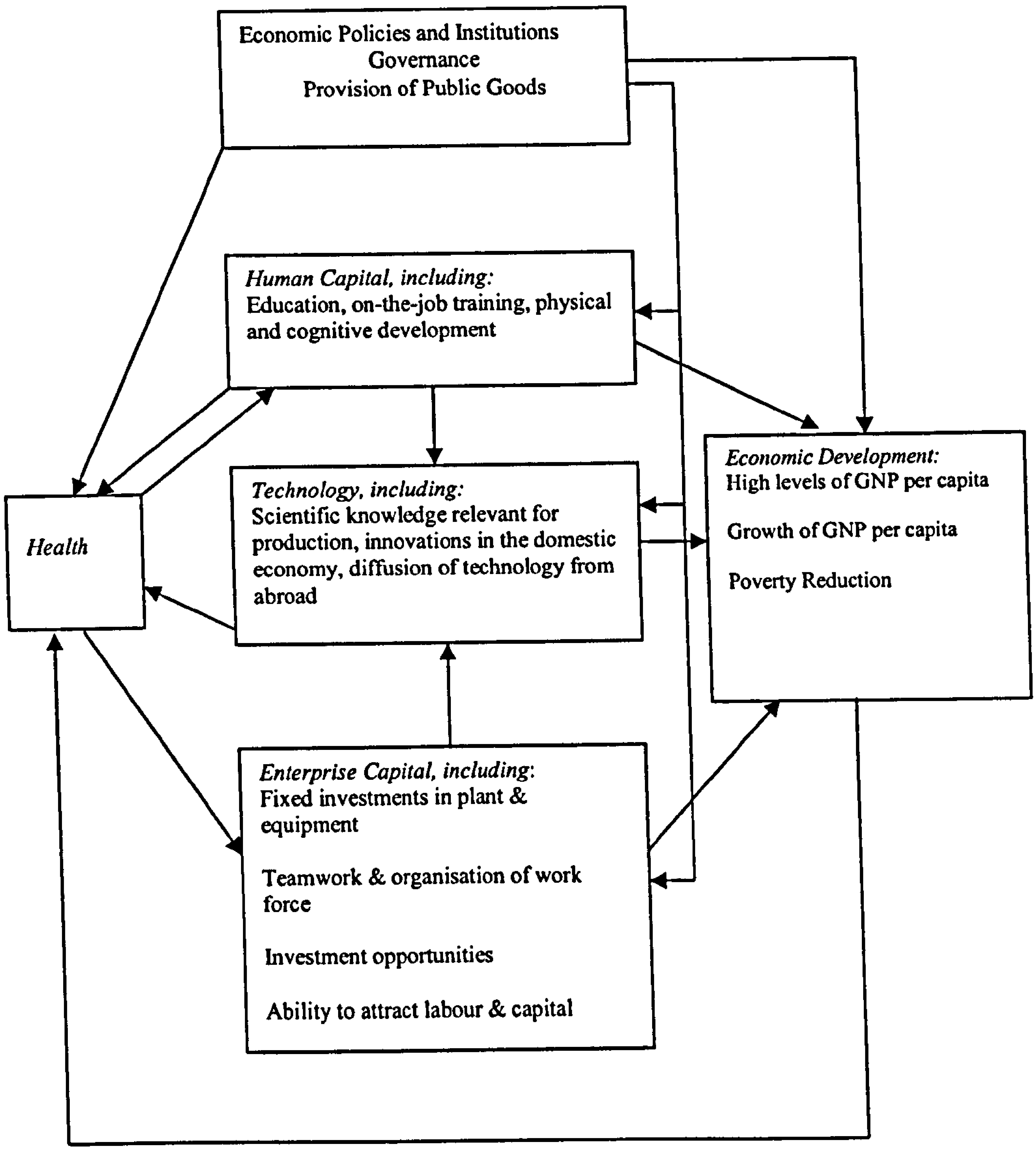
1.2.2 Health and development

While attaining health goals is an end in itself, their contribution to the achievement of the other development goals could be significant. In recognition of this, the World Health Organisation (WHO) Director-General established the Commission on Macroeconomics and Health (CMH) to assess the place of health in global economic development, with a particular focus on the link between health and poverty (WHO, 2001). The report argued that just as important as economic well-being, good population health is a critical input for poverty reduction. This is corroborated by a substantial amount of research that documents the divide in health status among high- and low-income groups in society (Hales, 1999; Gwatkin, 2000; Gallup & Sachs, 2001; Leon *et al.*, 2001).

A disproportionate amount of the global burden of ill-health is borne by low-income groups and has been attributed to a number of factors (Hales, 1999; WHO, 2001). First, chances of the poor getting sick are high because of their lack of access to clean water and sanitation, medical care, safe housing, education, information and adequate nutrition. Second, research suggests that they are less likely to seek medical care when sick because of poor financial and physical accessibility to health service providers and insufficient knowledge on how to respond to an illness episode. Third, out-of-pocket outlays for ill-health often constitute a huge proportion of poor household's income, and at times necessitate selling of income-earning assets. This may plunge a household into long-term poverty, which can be inter-generational. A summary of the position of health among the other contributors to poverty reduction is illustrated in Figure 1.1. Economic output is considered here to be a function of policies and institutions on the one hand, and factor inputs (human capital, technology and enterprise capital) on the other. Health is shown to have its most important economic effects on human and enterprise capital.

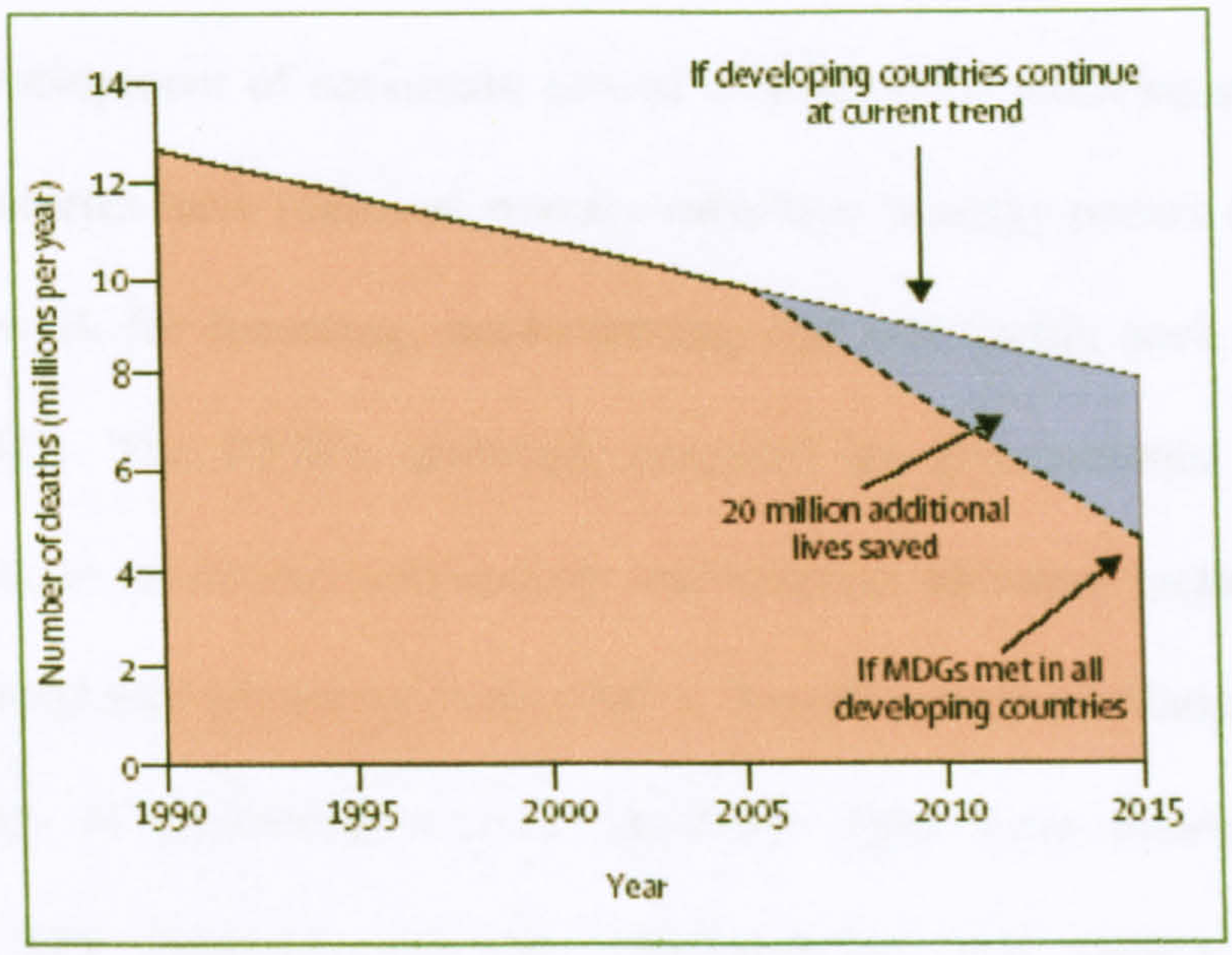
Three main channels, through which disease impedes economic development, have been identified. The first channel is the reduction of number of years of healthy life expectancy, resulting in considerable economic loss. This is particularly severe in low-income countries. Second, disease reduces the overall parental investment in children. Due to high mortality rates, couples produce large numbers of children to compensate. The resulting numbers put a strain on family resources affecting the health and education of each child. Third, ill-health has a depressing effect on business and infrastructure investment, not only by decreasing the productivity of individual workers but also the purchasing power of the whole society.

Figure 1.1 Health as an input into economic development (Source: WHO, 2001)



The UN Millennium Project report (2005), highlights that if the MDGs were achieved, 500 million people will be lifted out of poverty by 2015 and tens of millions of lives saved, with a greater proportion of the gain taking place in Africa (Sachs & McArthur, 2005; UN, 2005). With the MDGs on schedule, from now to 2015 about 30 million fewer children would die before the age of five, and about 20 million fewer will die compared to the current progress in combating child mortality (Figure 1.2). Central to attainment of the MDGs are health systems that meet the health needs of their populations, especially for the handful of conditions that contribute to the majority of the burden of ill health. The health goals depend primarily on access and use of preventive and treatment health interventions and services (Sachs & McArthur, 2005; UN, 2005). Access to these interventions and services in turn, depend on a number of factors as discussed later in Section 1.5, important among them being the ease with which people physically reach these services, especially in Africa where the transport infrastructure is poor.

Figure 1.2 Global mortality of children under 5 years of age (Source: Sachs & McArthur, 2005)



Although in this section the focus is on the role of health in poverty eradication, the importance of institutions, and bio-geographic factors that determine the development of good institutions, as described by Diamond (2004), are acknowledged.

1.2.3 Global efforts to implement the MDGs

The attainment of the MDGs requires a special partnership between high-income and low-income countries. Central to the UN International Conference on Financing for Development (ICFD) of March 2002 held in Monterrey, Mexico, were concerns over the dramatic shortfall in resources required to achieve the MDGs (http://www.un.org/esa). At the conference, the high-income countries reaffirmed their commitment to provide financial and technical support to low-income countries through foreign direct investment and other private flows, implement debt relief for some countries, ease international trade restrictions and enhance trade and technical cooperation. In addition, the low-income countries pledged to mobilise domestic resources and attend to systemic problems in public service, economy and governance to enable efficient utilisation of resources (UN, 2002).

As part of the overall strategies in implementing the MDGs, the Monterrey Consensus emphasised the development of nationally owned strategies for reducing poverty. To this end many poor countries have prepared poverty reduction strategy papers (PRSPs), which provide the framework for financing, implementing and monitoring such strategies (UN, 2002; UNDP, 2003). The PRSPs, although prepared by governments, emerged from participatory processes involving civil society and external partners, including the World Bank and the International Monetary Fund (IMF). Broadly, implementation of the MDGs is the responsibility of governments with significant input from financial institutions, bilateral donors, UN agencies, regional organisations, civil society and scientific community. Central to the PRSPs is the role of population health in poverty reduction, whose attainment is largely dependent on making resources and services available and accessible to the poor.

1.2.4 Global progress of health MDGs

One of the most comprehensive data on the global status of MDGs was published in the *Human Development Report* 2003 (UNDP, 2003). Most of the data collated were for 2001, when most countries were beginning to implement the MDGs. In the report, for each goal, countries were divided into top priority, high priority and low priority. Top priority countries were considered to be those that the starting levels for MDGs were very low and progress had failed over the years. These required the greatest attention and resources. The high priority countries were those where progress was still insufficient but were less desperate than the top priority ones. They were either making progress from low levels of development or making slow (or negative) progress from higher levels. Low priority countries were those that had already achieved the goals or did not have significant impediments to achieving them. Figure 1.3 shows the distribution of top, high and low priority countries globally. Out of the 31 top priority countries, 25 (81%) were in SSA, Kenya included. Fourty-six percent of high priority countries were from SSA.

The report showed that child mortality rates had increased in the 1990s, with rising rates in 14 top priority countries and no declines in a further 17. In some of these countries one third of children will not reach the age of five (Figure 1.4). For the under-five mortality MDG, none of the SSA countries are on target, with poor communities within countries making the slowest progress (World Bank, 2004a).

Figure 1.3 Distribution of top, high and low priority countries based on starting levels and status of MDGs (adopted from the Human Development Report, UNDP 2003)

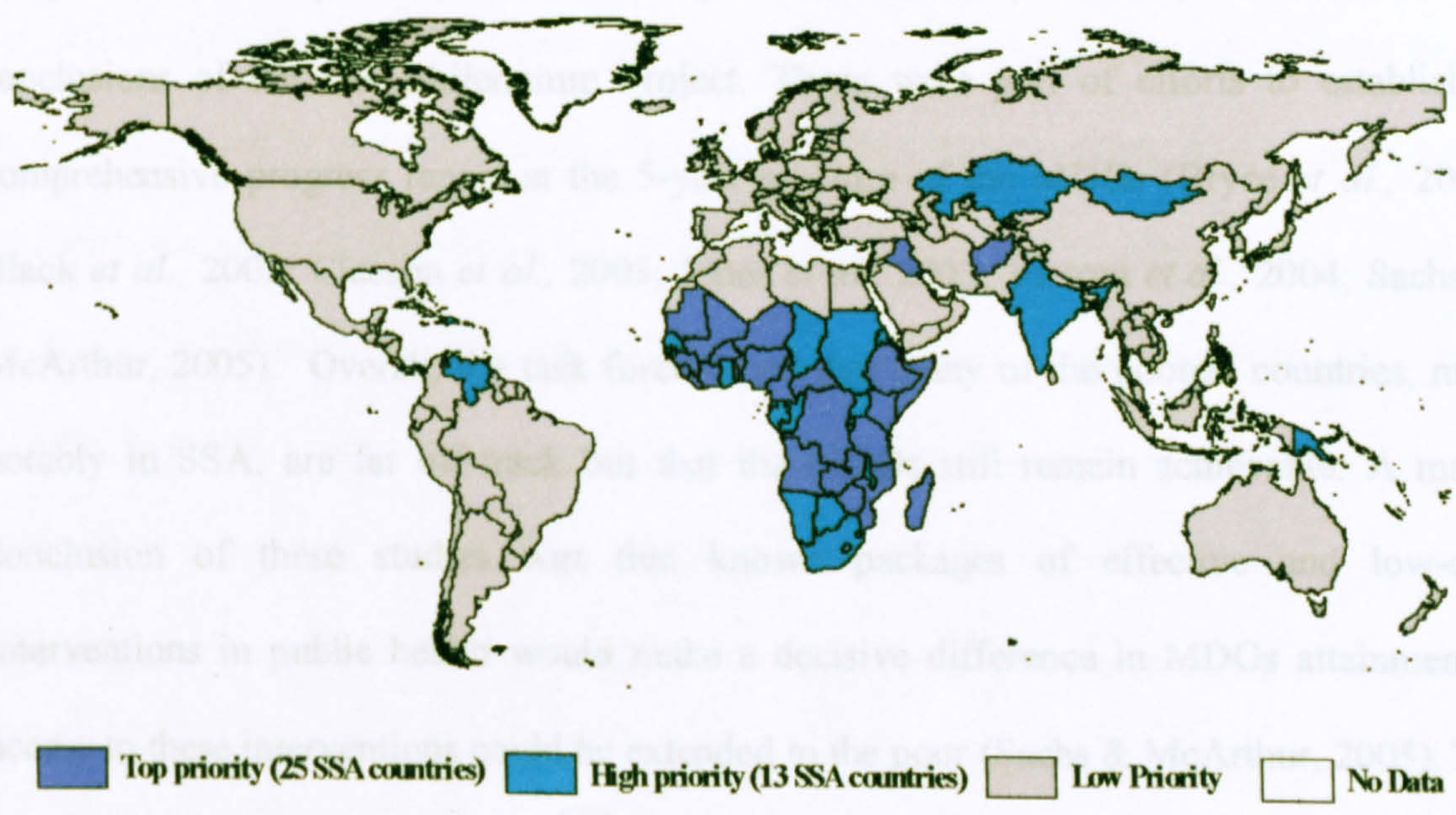
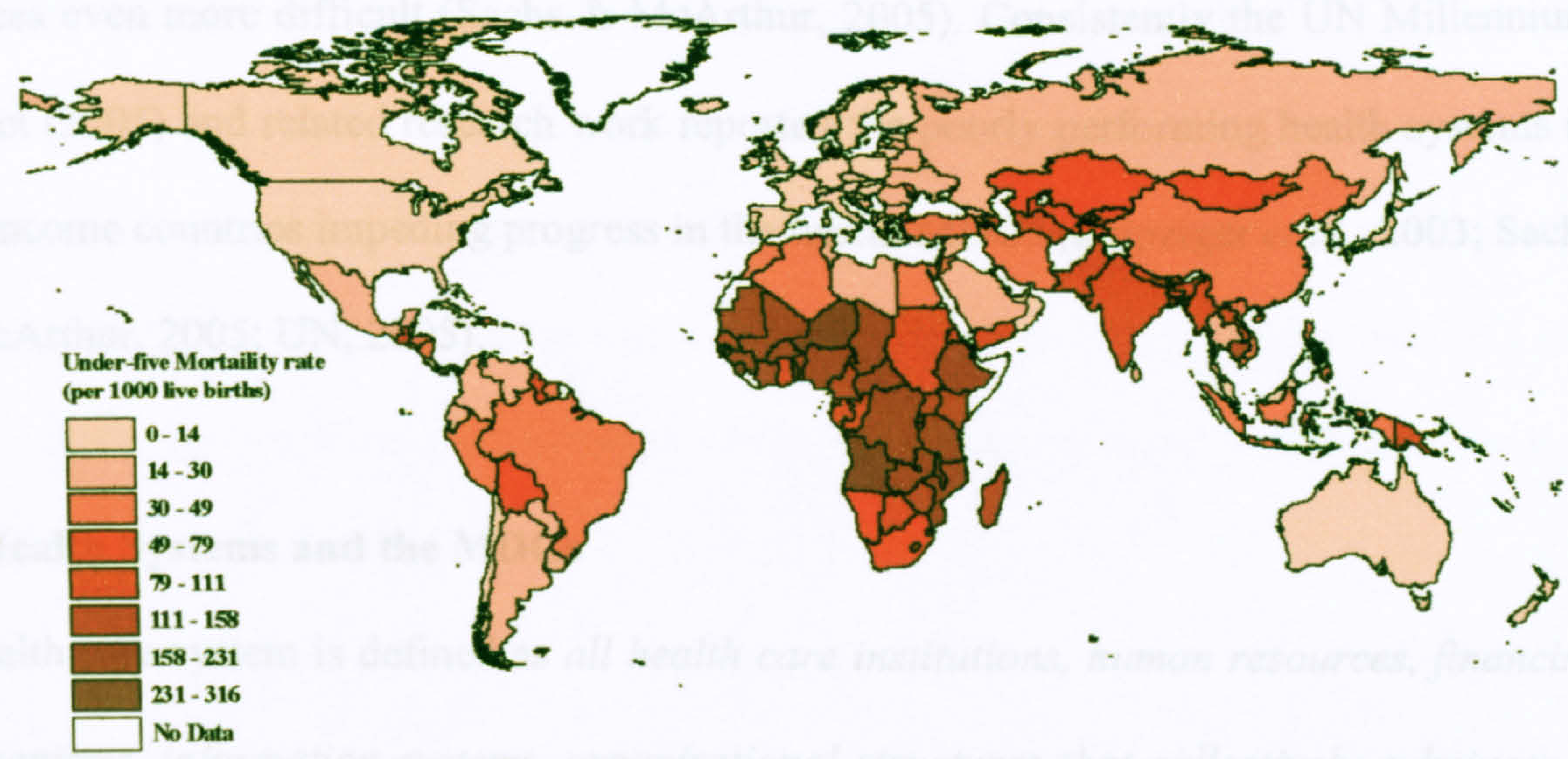


Figure 1.4 Infant Mortality rate (per 1,000 live births) 2001 (mortality data was obtained from http://hdr.undp.org/reports/global/2003/)



A series of papers have been published since the introduction of the MDGs, by a 3-year independent advisory task force initiated by the UN Secretary General, to summarise key conclusions of the UN Millennium Project. These were part of efforts to establish a comprehensive progress report at the 5-year juncture of the MDGs (Bryce *et al.*, 2003; Black *et al.*, 2003; Claeson *et al.*, 2003; Jones *et al.*, 2003; Victora *et al.*, 2004; Sachs & McArthur, 2005). Overall, the task force found that many of the poorest countries, most notably in SSA, are far off-track but that the MDGs still remain achievable. A major conclusion of these studies was that known packages of effective and low-cost interventions in public health would make a decisive difference in MDGs attainment if access to these interventions could be extended to the poor (Sachs & McArthur, 2005). The UN Millenium Project (2005) report identified four broad categories to explain why some regions are failing to meet the MDGs: 1) poor governance; 2) pockets of extreme poverty; 3) policy neglect; and 4) poverty traps. As a result, populations do not have access to key resources and services to overcome hunger, inadequate infrastructure and disease and are unable to achieve sustained economic growth (UN, 2005). In SSA, poverty traps were much more likely to occur due to adverse geographic conditions including: adverse disease ecology; adverse conditions for agriculture; and high transport cost which makes access to services even more difficult (Sachs & McArthur, 2005). Consistently the UN Millennium Project (2005) and related research work reported the poorly performing health systems in low-income countries impeding progress in the health MDGs (Leipziger *et al.*, 2003; Sachs & McArthur, 2005; UN, 2005).

1.3 Health Systems and the MDGs

A health care system is defined as *all health care institutions, human resources, financing mechanisms, information systems, organisational structures that collectively culminate in a health action* (Lassey *et al.*, 1997; WHO, 2000). The World Health Report (2000), which was devoted entirely to health systems, describes the objectives of a health system as two-fold: goodness (the best attainable average level of health), and fairness (the smallest feasible difference among individuals and groups). Goodness is achieved when a health system responds well to people's need while fairness is achieved when it responds equally well to everyone without discrimination (WHO, 2000). Aday and colleagues grouped the overall goals of a health system into effectiveness, efficiency and equity (Aday *et al.*, 1998). Effectiveness examines the benefits of health care measured by the improvements in health while efficiency relates these improvements to the resources required to produce them. Equity is concerned with health disparities and the fairness and effectiveness of the procedures for addressing them.

The general consensus is that health systems in low-income countries are performing poorly (WHO, 2000). The World Health Report (2000) used an index of health system performance to rank 191 nations. Of the 50 poorest performing nations, 43 were from Africa (Kenya was ranked 178 of 191). Many causes have been identified to explain the state of health systems in low-income countries. While the low level of available health resources (both in terms of recurrent and household expenditure) is a major problem, mismanagement of scarce resources, rapidly growing populations, an increasing burden of infectious diseases and the resulting cycle of poverty, have been cited as key concerns (WHO, 2000). In a study into health system constraints that impede the achievement of MDGs, it was concluded that in the 42 countries with 90% of child deaths worldwide in 2000, 63% of these deaths could have been prevented through full implementation of a few known and effective interventions which health systems have failed to deliver (Travis *et al.,* 2004).

An additional problem compounding the failing health systems has been the lack of a clear focus in health systems research aimed at devising ways of improving the performance of health systems. For instance, most international health policy debates in the 1980s and 1990s were dominated by health efficiency issues driven by health financing and resource generation. This promoted aggregate health status as the primary public health policy goal to be pursued through the health system (Gilson, 1998). While these changes resulted in increased health system efficiency, they also revealed considerable potential to harm health equity, although this impact has rarely been evaluated (Whitehead, 1993; Gilson & Mills, 1995).

It is in recognition of these challenges that renewed efforts have been made to reignite the position of health equity as a major concern in international and national public health (WHO, 1996a; Gilson, 1998; Leon *et al.,* 2001; McIntyre & Gilson, 2000). Creese (1998) argued that to ensure greater pursuit of health equity some of the processes required involve assessing the scale of disparities between geographical, sex, age and cultural groups.

A more recent task force convened by the WHO showed that in SSA and many other low-income countries, health systems constraints, particularly availability of relevant services and access to these services are impeding the attainment of the MDGs (Task Force on Health Systems Research, 2004). The task force suggested several topics for health-systems research and outlined their potential to affect the attainment of each of the 8 MDGs. Research into organisation and delivery of health services, particularly equity, efficiency and effectiveness of the health care system, under which issues of access and use of health services fall, were found to be relevant to at least 4/8 of the MDGs (Table 1.2).

A final conclusion of the task force was that while inequities in access to health care were well documented within low- and middle-income countries, little is known on how best to reduce these inequities to make effective health interventions available and accessible (Task Force on Health Systems Research, 2004).

Table 1.2 Suggested topics for health systems research and their potential to affect the targets for the attainment of the MDGs (Source: Task Force for Health Systems Research, 2004)

	MDG					
	1	4	5	6	7	8
Financial and human resources						
Community-based financing & national insurance	✓	✓	✓	✓		✓
Human resources for health at the district level and below	✓	✓	✓	✓		
Human resource requirement at higher management level	✓	✓	✓	✓		
Organisation and delivery of health services						
Community involvement	✓	✓	✓	✓	✓	
Equitable, effective and efficient health care	✓	✓	✓	✓		
Approaches to the organisation of health care	✓	✓	✓	✓		
Drug and diagnostic policies	✓	✓	✓	✓		✓
Governance, stewardship & knowledge management						
Governance and accountability	✓	✓	✓	✓	✓	
Health information systems	✓	✓	✓	✓	✓	
Priority setting and evidence-informed policy making	✓	✓	✓	✓	✓	
Effective approaches to intersectoral engagement in health	✓	✓	✓	✓	✓	✓
Global influences						
Effects of global initiatives and policies on health systems	✓	✓	✓	✓	✓	✓

Most international comparison in health inequality is made between socio-economic groups defined in different ways, for example based on income level, social class or educational level (Leon *et al.,* 2001). Despite differences in definition, a number of research groups have established real international variations in the magnitude of socio-economic differences in health status (Hales, 1999; WHO, 2001; Gwatkin *et al.*, 2004). Gwatkin *et al.* (2004) argue that most '*health systems are consistently inequitable, providing more and better quality services to the well-off, who need them less, than to the poor who are unable to obtain them*'. The greater health needs of the poor are perhaps best demonstrated in a study which showed that Africa had a 30 times higher under-five mortality than Europe (World Bank, 2003). A review of 21 countries in South America, Africa and Asia showed that the richest 20% of the population gained on average 26% of total financial subsidies provided through government health expenditures, compared to less than 16% in the poorest 20% of the population (Filmer, 2004; Gwatkin *et al.*, 2004). A household survey in four districts in Tanzania showed that health care-seeking among children under five years was worse in poorer than in relatively rich families even in rural communities which were regarded as uniformly poor (Schellenberg *et al.*, 2003). In other studies in Tanzania, Brazil and Bangladesh, it was shown that the richer children received several life-saving health interventions simultaneously whereas many of the poorest children failed to receive even one (Victora *et al.*, 2004).

In this section the MDGs, their progress thus far, diagnoses of the impediments to their attainment and the role of the health system and its health equity functions, particularly in ensuring access to relevant resources and services, have been outlined. In the next two sections the definition and broad concepts of health equity are presented. Methods of defining health equity with particular emphasis on the role and access and utilisation of health services are discussed.

1.4 Health Equity

Equity in health has been defined and conceptualised in several ways, as its principles derive from a variety of fields including ethics, public health, medicine, economics and others (Macinko & Starfield, 2002). Driving these definitions is the idea that certain health differences or inequalities are unjust or unfair and constitute health inequities. However, because justice and fairness can be interpreted differently by different people in different settings, it is possible to define equity in many different ways. A definition of health equity adopted by the International Society for Equity in Health (ISEqH) is, '*the absence of systematic [and potentially remediable] differences in one or more aspects of health status across socially, demographically, or geographically defined populations or population subgroups*'.

The determinants of health equity are those that impact on the individual's or communities' health status and can be grouped into four broad categories: a) socio-economic, b) demographic, c) geographic, and d) policy and governance (WHO, 2000; Macinko & Starfield, 2002).

A number of published studies have examined inequities in health based on a variety of markers and methods using variables such as financial and non-financial barriers of access to health services, equity of benefits, equitable financing, efficacy, effectiveness and quality of care, administrative efficiency, democratic accountability and empowerment, and several other socio-economic indicators (Daniels *et al.*, 2000; van Doorslaer *et al.*, 2000; Turrel & Mather, 2001). Others such as Waters (2000) and Low *et al.* (2003) argue that population or individual's health status, which is commonly used as an indicator of health inequity, is difficult to measure with precision and distributing health resources in order to equalise health status would in some cases be neither efficient nor cost-effective. Instead they advocate for the use of access and utilisation of health services as a measure of health equity and performance of health systems. This thesis, therefore, is an attempt to assess the health service access and utilisation aspect of health equity, with a particular emphasis on the spatial variables. In the next section, the concept, definition and determinants of access and utilisation of health services are presented with a greater emphasis placed on distance and related variables.

1.5 Access and utilisation of health care as a measure of health equity

Central to achieving the health MDGs is an equitable health system. The main determinants of health equity are either socio-economic or geographic, and impact on the individuals' health status either by reducing or increasing their likelihood of getting sick or accessing appropriate health care when sick (Ensor & Cooper, 2004). However, current methods of health equity focus mainly on the individual or population's health status. While measuring equity as equality of health status has intuitive appeal, the practical difficulties of measuring health status with precision are well-documented (Low *et al.*, 2003; Waters, 2000). In addition, the policy product of such an approach is, by implication, to distribute health resources to equalise health status and this can, in some cases, be neither efficient nor cost-effective. Access and utilisation of health services has been recognised as a significant contributor to the attainment of MDGs (Section 1.2). As such, measures of access and utilisation of health services have been suggested as indicators of health equity instead of the traditional measures of health status (Waters, 2000). In this section the definitions and concepts of access and utilisation of health services are established. The role of geography and in particular the concept of distance to services is emphasised as these constitute the central theme of the thesis.

1.5.1 Access to and utilisation of health care- definition and determinants

The Concise Oxford English Dictionary, 10th edition, defines access as the 'right or opportunity to use something'. In health services research, most of the literature focuses on the correlates of access and on outcome measures such as service utilisation and patient satisfaction (Aday & Andersen, 1975; Ensor & Cooper, 2004). In the 1970s the US Federal Agency made an attempt to define access to health care based on a synthesis of the literature. Penchansky (1977) and Penchansky & Thomas (1981) were assigned this task and defined access in terms of the effects of interaction between characteristics of the individual and relevant health services.

Ensor & Cooper (2004) grouped the factors that operate at the level of health service provider and impede the utilisation of health services as supply-side barriers. These factors are related to the production of effective health care services and the focus is on the availability of skilled staff, medical supplies, infrastructure and protocols of treatment. Those user factors which act at the individual, household or community level were classified as demand-side barriers. These include physical and financial accessibility, age, gender, race and ethnicity, perception, awareness and education and other socio-cultural norms. Access is considered to exist when these factors are optimally aligned for a particular health care context. Penchansky & Thomas (1981) defined five dimensions of access to health services that illustrate how these factors relate:

> *Availability*- the relationship of the volume and type of existing services and resources to the user's volumes and type of needs
>
> *Accessibility*- the relationship between the location of supply and the location of users, taking account of the user transportation resources and travel time, distance and cost
>
> *Accommodation*- the relationship between the ways in which supply-side resources are organised to accept users in terms of appointment systems, hours of operation, walk-in facilities and existing patient provider relationship to the users' ability to accommodate to these factors and the users' perception of their appropriateness
>
> *Affordability*- the relationship of prices of services to user's income, ability to pay, eligibility for public support and insurance. Users' perception of worth relative to price or total cost may also be a relevant concern

Acceptability- the relationship of the users' attitudes about personal and practice characteristics of providers to the actual characteristics of existing providers as well as to provider attitudes about acceptable personal characteristics of patients

These dimensions of access are compatible with the WHO access framework that identified geographical accessibility, financial accessibility, cultural accessibility and functional accessibility (WHO, 1978). Khan & Bhardwaj (1994) described access in terms of spatial and aspatial aspects. The spatial aspects relate to the geographic or physical factors while the aspatial aspects refer to the socio-economic barriers or facilitators of access to health care. An important measure of access is its outcome in terms of utilisation of health services, which in turn depends on understanding the behaviour and characteristics of users. In the next section, a brief description of the aspatial determinants of access and utilisation of health services is given. This is then followed by a detailed review of the spatial factors, a reflection of the core theme of this thesis.

1.5.2 Aspatial determinants of access and utilisation of health services

The aspatial factors that influence access and utilisation of health services include the cost of treatment, education and information, community and household barriers and quality of health services (Ensor & Cooper, 2004).

Cost of treatment has been recognised in several research works to deter users from accessing health care. A study carried out in China by Gertler *et al.* (1987) showed that while demand for health services was equal among different income groups, people in the lowest income quintile were highly responsive to price changes in health services impeding their access to these services. Other studies on the introduction of user fees in Ghana, Swaziland and Zaire showed cost of services generally reduced service demand (Waddington & Enyimayew, 1989; Yoder, 1989; de Bethune *et al.,* 1989). Rous & Hotchkiss (2003) showed, in a study in Nepal, that cost of treatment had a significant effect on the type of services chosen with the poor resorting to cheaper home-based or traditional treatment. In Tajikistan, Falkingham (2004) found that out-of-pocket payments for healthcare exacted a heavy toll on poorer households forcing many of them into debt.

The level of education, measured as the number of years of schooling, has been shown to be the most important correlate of good health and determinant of maternal and child survival (Grossman & Kaestner, 1997; Cleland & van Ginneken, 1988; Ragupathy, 1996; Agha, 2000). In Tanzania and Guinea education and information have also been found to determine patients' expectation of service providers relating to quality of services which in turn influenced the use and choice of health services, with patients using what they perceived as better quality services relative to their knowledge of these services (Leornard *et al.*, 2002; McFadden & Sunkara, 2004).

The community or household factors that may impede or facilitate health service use include gender, age, race and ethnicity, religion and income. Several studies have reported gender biases in utilisation of health services with the female population groups having a higher utilisation rate than male in most cases (Field & Briggs, 2001; Pokhrel & Sauerborn, 2004; Thorson *et al.*, 2000). In Tanzania it was reported that men were more likely to be given preferential treatment in access to health care over women (Narayan, 1997). Pillai *et al.* (2003) also reported that in Kerala, India, boys were more likely to be treated in the alternative medical sector (non-allopathic) as opposed to girls. Cultural and religious beliefs also have an impact on the decision to seek health care. Cultural restrictions on the movement of women and perception of child birth, illness and appropriate treatment have been shown to influence the utilisation of health services (Mwenesi, 1993; Ndyomugyenyi *et al.*, 1998; Bhatia & Cleland, 2001; Rashid *et al.*, 2001).

Household income level is an important consideration in the choice of treatment as it determines the ability to pay for health services. A considerable amount of research reveals that the poor bear the greatest burden of disease and benefit the least from health services (Demery, 2000; Makinen *et al.*, 2000; Hjorstberg, 2002; Pillai *et al.*, 2003; Rous & Hotchkiss, 2003; Falkingham, 2004). In Cambodia, due to low treatment costs and abolishment of informal fees, the poor used health services more often than the better-off (Yanagisawa *et al.*, 2004). Diop *et al.* (1998) reported that in Zambia while a prepayment scheme improved access to health services, the highest income quintile made up 49% of the participants while only 12% of the participants came from lowest income quintile.

The expectations of populations in terms of quality of health care are also central to their use and choice of health services. Factors such as: technical competence of health care personnel; interpersonal relations between patients and care providers; availability and adequacy of resources; accessibility; and effectiveness of care have been reported to greatly influence the use and choice of health services (Haddad *et al.*, 1998; Lule *et al.*, 2000; Aldana *et al.*, 2001; Leornard *et al.*, 2002; Boller *et al.*, 2003).

1.5.3 Spatial determinants of access and utilisation of health services

The spatial factors that impact on health services are derived from the relationship between the location of health services and the location of users, taking account of the users' transportation resources and travel time, distance and cost. There is much evidence to suggest that distance to health services imposes a considerable cost on individuals and households and that it may decrease the use of health services in developed countries, developing countries and especially Africa.

1.5.3.1 The evolution of the concept of distance in access and utilisation of health services

Interest in the concept of distance in access and utilisation of health services can be traced back to more than 70 years in the published literature. In a seminal review into the concept of distance in access and use of health services, Shannon *et al.* (1969) report that the earliest application of distance in medical care research was by Lively & Beck (1927), who noted the tendency for utilisation of physician services in Ohio to decrease with increasing distance from physician. Most other publications at this time dealt with the unequal distribution of health personnel or facilities relative to population for different areal units (de Vise, 1966). In general, it was found that health personnel were most numerous relative to population in urban areas where areal units were smaller. As a result, it was concluded that rural populations, which had access to fewer health personnel and facilities and were sparsely distributed over large areas, had to travel greater distances to health services. Distance was therefore not measured explicitly.

During the 1930s, several studies dealt more directly with the impact of distance on utilisation of health services, all of which were carried out in rural settings in the USA (McCormick, 1934; Wilson *et al.*, 1938). The main results of these studies were that patients in rural areas travelled longer than urban patients to health services, on average 8 to 10 miles to see a physician and that the 'decay function' of medical utilisation was not related to either increase or decrease in rate of illness. Several limitations of the research during this period included the use of mid-point of towns to represent the location of populations and health services, thereby ignoring the measurement of any travel within these towns. The practice at the time of non-random physician home visits also compounded the problem of measuring distance to health services (Shannon *et al.*, 1969).

An impetus into the investigations of the distribution and utilisation of medical services was provided by the enactment of the Hospital Survey and Construction (The Hill-Burton)

Act of 1946 in the USA (USPHS, 1961). The purpose of the legislation was to assist states to provide 'adequate hospital, clinic, and similar services to all people'. This was accomplished in two phases: 1) survey of existing health services and development of a plan of health needs, 2) construction of health services. The first phase of this legislation stimulated interest in the distribution of health services and analysis using the distance parameter. Several studies followed investigating the impact of distance on health service use (Mather, 1948; Thaden, 1951; Fein, 1954; Terris, 1956; McNamara & Hassinger, 1956; Shannon *et al.*, 1969).

A study by Jehlik & McNamara (1952) was probably the first one solely concerned with relationship of distance to utilisation differentials of various health personnel and facilities. The study tested whether distance to health personnel and facilities was inversely related to use of these services and positively related to the incidence of morbidity at their homes. The effect of distance among rural and semi-rural areas was also compared. The study showed that people who lived at greater distances to health services made use of them more for curative than preventive purposes and distance from physician was positively correlated with incidence of morbidity.

The first attempt at defining medical service areas using distance was carried out by Cioco & Altman (1954). The study was noted for the development of a quantitative index for defining medical service areas and the sophistication with which distance was measured. The authors emphasised the need to measure available medical services in relation to actual population served and that knowledge of the pattern of movement for medical care was a prerequisite to the delineation of service areas. The treatment of the distance factor was quite sophisticated relative to previous work (Shannon *et al.*, 1969). They not only noted that the frequencies with which people travelled to physician services were relatively high in the interval under 5 miles, fell off at first with increasing distance, and then tended to level off, but gave the relationship a mathematical form. A hyperbolic function ($y=a/x^b$) was utilised, expressing the idea that the frequency with which distance was travelled varied inversely as some power of the distance travelled.

Following this study, instead of the representation of frequency distribution of service use and facility distribution, the first steps to delineate medical service areas and treat distance factor mathematically were established (Shannon *et al.*, 1969). This led to the use of rational rather than empirical distance models, particularly based on economic demand functions, where an area's demand for health services was considered to vary directly with population size and income and inversely with the relative cost of travel. Because of the need to incorporate travel cost, the characteristics of the transport media that influenced the demand for health services were required. The use of the transportation network in health service accessibility and utilisation modelling was initially driven by the analysis of optimal location of health services. One of the earliest attempts to find optimal locations of hospitals was in Sweden. 'Isochronal' (time) lines for various models of transportation were established around major cities in order to find the most suitable location, in terms of population served and the amount of travel time to hospitals (Godlund, 1961). Prior to this, distance was predominantly measured as straight-line or as self-reported travel time. Later the differences in health service types were incorporated into such models (de Vise, 1966).

1.5.3.2 Distance in access to and use of health services in high-income countries

In a more recent review of the literature, it was shown that most of the research work in spatial determinants of access and utilisation of health care were conducted in Western Europe and North America (Twigg, 1990; Openshaw, 1996). Among rural communities in the USA, distance from a patient's home to the health facility was an important determinant of differences in utilisation of health service use: the further patients were from health services the lower their utilisation of these services (Fielder, 1981). Lucas &

Rosenthal (1992) carried out a study in a rural community in the state of New York and found that a distance of ≥20 miles negatively affected the use of health services and was significantly associated with the patients' satisfaction. Another study found that patients living >20 miles away from a hospital were also much less likely to visit ambulatory services for after-care following myocardial infarction (Piette & Moos, 1996). A study in the UK showed that accessibility and utilisation of health services varied greatly in response to mobility and locational characteristics (Field & Briggs, 2001). In Scotland, as distance from a cancer centre increased the chances of diagnosis reduced and was associated with poorer survival rates (Campbell *et al.,* 2000). In Canada, 76% of cancer patients surveyed indicated that treatment clinics closer to home was a necessity but only half of these patients felt this need was being met (Canadian Cancer Society, 2003). In a study in South West England, Jordan *et al.* (2004) showed that rates of premature limiting long-term illness were highest in areas most distant from hospitals.

1.5.3.3 Distance in access to and use of health services in low-income countries

In the low-income settings, Kumaran (1983) attempted to measure locational efficiency of health services in Madras, India, using data on utilisation patterns which showed that generally use declined with distance. Among the variables determining use of health services, distance was found to be the most important, followed by cost of services and quality of care. In the rural Bendel State of Nigeria distance to hospitals was used as a measure of accessibility which was then used to define Local Government health areas (Okafor, 1984).

In Papua New Guinea (PNG), Garner & Giddings (1985) developed a health facility usage index around a rural health centre which served a population within a radius of 40 km. This catchment area was divided into 10 km concentric zones and population for each zone was calculated from a census. A value of usage index greater than one in a zone indicated that it contributed a greater proportion of patients than its population contributed to the total catchment population. The usage index showed that patients living closer to the health facility used it more than those further away, but this varied with diagnosis, with diseases such as malaria having a usage index of two within the 10 km zone. In a similar study in rural PNG, Muller & colleagues estimated distance decay effects of attendance rates around a health centre. Attendance markedly decreased with distance both overall and with conditions such as malaria and acute respiratory infections. There was a 50% decrease in use of the health centre at 3.5 km radius, with spatial patterns accounting for 32% in variation of age and gender specific attendances (Muller *et al.*, 1998).

In Kingston, Jamaica, car ownership among high-income groups afforded them a considerable choice of health service providers and generally had higher utilisation rate than the low-income groups. The distance at which public health services were located was the main determinant of health care seeking among low-income respondents. The highest proportion of patients using the nearest facility was in places where there were fewer health outlets. In one hospital, 50% of respondents who attended it incorrectly believed that it was the facility nearest to them (Bailey & Phillips, 1990). In Cambodia additional increase in health service use due to reduction of charges was seen only in villages located within 2 km from health services, while those further than away reported no changes in service use (Yanagisawa *et al.*, 2004). In northeast Brazil 25% and Burkina Faso, 28% of the total patient cost was spent on transport to and from health services (Sauerborn *et al.*, 1995; Frew *et al.*, 1999).

In the World Bank *World Development Report* 2004, affordable access to health services for the poor was found to be low and contributing to this were large distances to service points and poor transportation infrastructure in predominantly rural communities. In a study of 20 mostly African countries presented in this report the poorest fifth of the population was found to live at greater distances from health facilities compared to the richest fifth of the population as shown in Table 1.3. In some countries this disparity was more than five fold (World Bank, 1994). These measures of distance access to health services for the 20 countries were derived from demographic and health surveys. In the survey tools, three primary questions were asked to estimate distance or time to health services: 1) How far is the health facility from here (in km)?; 2) What is the most common type of transport to the health facility?; 3) How long does it take to get there using the most common type of transport?

Table 1.3 Mean distance to the nearest health facility among the poorest and the richest quintiles in 20 low-income countries[1] (World Bank, 2004b)

		Distance to the nearest health facility (kilometres)		
	GNI per capita	Poorest fifth	Richest fifth	Ratio
Bangladesh 1996-97	374	0.9	0.7	1.3
Benin 1996	395	7.5	2.8	2.7
Bolivia 1993-94	1004	11.8	2.0	6.0
Burkina Faso 1992-93	336	7.8	2.6	3.0
Central African Republic 1994-95	819	14.7	7.7	1.9
Cameroon 1991	611	7.0	5.4	1.3
Chad 1998	250	22.9	4.8	4.8
Ivory Coast 1994	788	10.5	3.4	3.1
Dominican Republic 1991	1261	6.3	1.3	5.0
Haiti 1994-95	336	8.0	1.1	7.2
India 1998-99	462	2.5	0.7	3.6
Madagascar 1995-96	303	15.5	4.7	3.3
Mali 1995-96	281	13.6	6.7	2.0
Morocco 1992	1388	13.5	4.7	2.9
Niger 1998	217	26.9	9.7	2.8
Nigeria 1999	266	11.6	1.6	7.1
Senegal 1992-93	933	12.8	10.0	1.3
Tanzania 1991-92	224	4.7	3.0	1.6
Uganda 1995	290	4.7	3.2	1.5
Zimbabwe 1994	753	8.6	6.3	1.4

1. Gross national income (GNI) per capita is that at the time of the survey expressed in 2001 dollars. Health facility encompasses health centres, dispensaries, hospitals and pharmacies.

A key limitation of this approach of measuring physical access to health care is that the estimation of distance, the time taken to reach health services and speed of the various types of transport media are based entirely on the perception of the respondents. As shown in the case of a hospital in PNG in which 50% of respondents thought they were attending the nearest health facility while in reality they were not (Muller et al., 1998), the respondents' perception of distance can be grossly incorrect. Considering how important the demographic and health surveys are in setting development agenda in the respective countries, the amount of uncertainty around the estimation of access to health care derived from the survey data has far reaching implications in measuring progress toward attaining the MDGs. However, an important advantage of this approach is the low cost associated with collecting information on travel time to health services compared to the alternative spatial approaches which require detailed geographic data.

Even when considered together with other determinants of access and utilisation of health services, distance was shown to have a significant influence. A report on household health seeking behaviour in Zambia concluded that regardless of the user fees charged at any given institution, the use of services diminished greatly with increases in distance at which potential users lived (Diop *et al.,* 1998). In Nigeria, Atting & Egwu (1991) carried out an investigation into indicators of accessibility to primary health care (PHC) using a structured questionnaire administered to mothers or household heads. About 27% of the respondents perceived distance to health services as impediment to service use. Another study in Zambia by Hjortsberg & Mwikisa (2002) showed that long distances to health services made it difficult for rural dwellers to seek medical care, especially during farming seasons. In Ghana, Buor (2003) showed that in Kumasi distance had a strong inverse relationship with utilisation of health services while travel time and transport cost showed a weak negative and positive association with utilisation respectively. In Burkina Faso, distance from health services was shown to be strongly correlated with infant and child deaths, with mortality highest further from health services (Becher *et al.,* 2004). In all these studies, distance was measured as self-reported travel time, transportation cost or user's estimation of actual distances.

Distance not only increases the time taken to reach health services but also contributes to delay in a decision to seek care as shown in a study in Vietnam (Ensor, 1996). Women's choice of place of delivery showed that distance was a major factor in the decision of women to deliver at home in the Philippines and Uganda (Schwarz *et al.,* 1993; Amooti-Kaguna & Nuwaha, 2000).

Another aspect of distance to health services is its contribution to opportunity cost of consuming health care. Both patients and caretakers take time off productive work in order to receive treatment and this represents an important cost particularly during peak periods of economic activity. Opportunity cost was shown to determine the success of compliance among different groups. In Pakistan compliance was more easily improved among the economically inactive as they had more time to seek care (Khan *et al.,* 2002). Akin & Hutchison (1999) reported that in Uganda, the poor were more willing to travel greater distances to health services than the rich; perhaps because their opportunity costs were lower.

Increasing distance from health services is in some instances associated with increased "information cost" particularly in rural settings where health facilities are often located in the region's densely populated and economically active localities where information is most easily available (Acton, 1975). Where increasing distance from a health facility is a measure of remoteness, populations living further away from the facility will be less likely to have access to information thereby limiting a patient's awareness and use of health services.

While the bulk of studies dealing with distance to health services show that it is an important determinant of health service use, a few studies have suggested the opposite. In a study in West Java, Indonesia, Sutrisna *et al.* (1993) found that when other factors were controlled for in a regression model, distance to health services was not associated with whether or not medical care was sought for ill children under the age of five. The age of the child and the duration of illness were found to be the important determinants of service use. In a similar study in Pakistan, cost of treatment, and not distance, was found to be the main determinant of use of government health services for treating children (Noorali *et al.*, 1999).

In Kenya, Airey (1989, 1992) examined the effect of road construction on the catchment area of two church hospitals. It was hypothesized that the new road would reduce the spatial and travel cost relationships for the hospital's out-patients and in-patients. Analysis of the data suggested that the distance-reducing effect of the new road was more important than its effect on travel costs and did not significantly change the spatial pattern of patient utilisation. Institutional barriers, particularly the economic barrier of fee-paying treatment, were found to be the main explanation for this finding. However, a limitation of these studies was that the location of patients' residences was not known and an increase or decrease of patient uptake at the health facility was used as a proxy for the effect of distance. Construction of the road could have increased patients access to alternative sources of treatment thereby drawing a certain proportion of regular users away from the health facility and any net gain in uptake at the health facility would have been difficult to deduce. In contrast, a study conducted by Snow *et al.* (1994) in Kilifi, Kenya, into factors influencing hospital use for childhood terminal illnesses showed that children who were admitted at the hospital tended to live nearer a bus stage than those not admitted while those further away made greater use of traditional healers and had higher mortality rates.

In summary, the relevance of distance and related spatial variables in the published health care research is well established. Its importance in defining access and use of health services, and subsequently monitoring the MDGs, particularly in SSA where the health and transportation infrastructure is poor, cannot be over-emphasised. The use of distance in defining health service areas and the potential of these for resource allocation have also been described. Nevertheless, due to the problems of measurement, the meaning of distance is not well understood. Often zones around health facilities based on straight-line distances are used to delineate health service areas, thereby ignoring the actual transportation media that people use. In other instances, the patients' perception of distance or travel time and the cost of transport are used to estimate access despite all the associated limitations. Where the capacity for improvement exists, data quality is often a problem. Recent trends in health service research, however, show an increasing sophistication in the way distance is measured. In the next section, the various methods used in defining spatial accessibility, their limitations and potential for improvement are discussed.

1.6 Methods and limitations of modelling spatial accessibility

Spatial accessibility (SA) refers to the combination of two dimensions of access to health care; a) location and distribution of health services (availability), and b) the ease with which one can physically reach those services (accessibility) (Khan & Bhardwaj, 1994; Luo, 2004).

While disparity in the spatial distribution of access to health care providers has been recognised as an important contributor to health inequity, efforts to quantify the problem have been hampered by the lack of satisfactory measurements and methods. From the published literature, measures of accessibility can be classified into four categories: 1) provider-to-population ratios; 2) distance to the nearest service provider; 3) average distance to a set of providers; and 4) gravitational models of provider influence (Guagliardo *et al.*, 2004; Wang & Luo, 2004).

Provider-to-population ratios are good for gross comparisons of supply between geographic units or service areas and are often used by policy analysts to set minimal standards of supply and identify under-served areas, for example, 1 health facility for 10,000 people (Connor *et al.,* 1995). A problem with provider-to-population ratios is that they ignore patients' border crossing, that is, the overlap of use of contiguous health service areas. They are also blind to variations in spatial accessibility within facility catchments and do not explicitly incorporate the distance dimension of access thereby assuming homogeneity in distribution of both population and health services (Guargliardo *et al.,* 2004).

Distance to nearest health services had been widely used as a measure of access to health care and has some merit in large geographic areas with few providers (Fryer *et al.,* 1999). However, it ignores the effect of the full array of service providers, especially where their density is high. As a way of overcoming this, average distance to all providers within a system in a defined geographic area has been used as a combined measure of accessibility and availability (Dutt *et al.,* 1986). However, this approach overweights the influence of peripheral facilities which are of no practical use to patients living on the opposite end of a geographic unit. Moreover, the use of nearest distance approach, be it in its discrete or average format, makes the assumption that people will always choose the nearest facility, which may not be true.

An approach used to resolve the limitations of these methods described above is the use of 'gravity models'. These were initially developed for land use planning (Hansen, 1959). They are a combined indicator of distance and availability and provide a more comprehensive measure of spatial accessibility. This is based on the potential interaction between any population point and all service points within a reasonable distance. The general formula of gravity based accessibility model is;

$$A_i = \sum_j \frac{P_j}{d_{ij}^{b}} \quad \text{Equation 1.1}$$

A_i is spatial accessibility from population point *i,* and P is the service capacity at provider location *j* and reflects the number of providers at that point and their combined capacity for health care provision. The distance between points *i* and *j* is represented by *d* and *b* is the gravity decay coefficient or the travel friction coefficient which represents the difficulty in travel for any given distance. Accessibility improves as the number and capacity of service providers increase, and distance or travel time to service points decreases (Guagliardo *et al.,* 2004).

While the gravity model is a good way of measuring accessibility variation, there are a number of problems associated with it. The value of the decay coefficient is seldom known, particularly for health services (Talen & Anselin, 1998). Very often a value of 1.0 or 2.0 is used, assuming that service attractiveness decays at a constant rate with increasing distance (Joseph & Bantock, 1982). In a phenomenon that is as varied as service use, it is unlikely that the decay rate will be linear and may actually be exponential depending on many factors such as the type of services and utilisation patterns of the client population. A second problem with the gravity model is its scale cannot be easily understood, particularly by health policy makers used to "policy-friendly" outcomes (Guagliardo *et al.,* 2004).

Luo (2004) used a floating catchment method (FCM) to assess areas of physician shortage in the US. This technique required only the location and counts of population and the location and numbers of physicians. Instead of using predefined administrative areas to compute physician population ratio, FCM defines the basic unit within which to calculate this ratio as a circle of defined radius centred on a population point. However, the distance of the radius used was intuitive and not based on empirical data. Another problem with the FCM was that population had to be aggregated to a point. While this might work well for small areas, aggregating large area population to a point introduces large uncertainties. Third, the methods did not account for cross-border use of physician services. Wang & Luo (2004) used a modified FCM method which they named the two-step FCM to overcome the cross-border use of contiguous service areas. This method essentially repeated the floating catchment twice, once on the population point and then on the physician point. First, for each physician location all population points were searched that were within a threshold of travel time and physician-to-population ratios were computed. Next, for each population location, all physicians within a threshold of travel time were computed and the physician-to-population ratios were summed.

Most of the research in spatial accessibility, regardless of the approach used, defines distance based on the straight-line but there is the potential for bias if straight-line distance does not accurately reflect travel time. Phibbs & Luft (1995) computed travel times for unimpeded travel between major intersections in upstate New York and compared with straight-line distances between these points. The correlation between distance and travel time was 0.987 for all observations and 0.826 for distances less than 15 miles. Although these very high correlations might indicate that straight-line distance is a reasonable proxy for travel time in some hospital demand or choice models, this was asserted with caution as suitable mainly in areas with large numbers of hospitals. The authors' outlier analyses show some exceptions, however, that the relationship may not hold for studies focusing on specific hospitals, very small numbers of hospitals, or studies in dense urban areas with high congestion and reliance on surface streets. As such, the congruency between straight-line distances and travel time is likely to be even poorer in large rural areas in SSA where the transport infrastructure is poor and services are sparsely distributed.

Modelling spatial accessibility, especially in underdeveloped areas, therefore, requires a definition of distance that is based on the actual routes people use in any given context and how their movement is influenced by the interaction of the various factors that affect mobility. Second, the representations of service and population locations are often at a coarse resolution. For instance, some studies rely on health service providers positions derived from facility zip code or street address and large area population data represented as a point. Third, most studies model potential/theoretical access and define accessibility purely by distance to nearest service providers ignoring the variation in actual utilisation of health services that is influenced by non-distance factors, which nonetheless, can be captured spatially.

Two recent attempts at defining distance better were undertaken by the WHO through its Pan-American Health Organization (PAHO) and Evidence and Information for Policy (EIP) groups. The PAHO group developed a model called SIGEpi which attempts to incorporate data on population, land cover, transport network, elevation, administrative boundaries and health facility location (http://ais.paho.org/SIGEpi). The second model developed by EIP called AccessMod is essentially similar in approach and data requirement to SIGEpi. However, AccessMod is raster-based while SIGEpi is a vector-based approach (Black *et al.*, 2004). A third model called AccessPlan was developed by a group at the University of Waterloo, Canada, and is similar to SIGEpi and AccessMod in approach (http://www.fes.uwaterloo.ca/Tools/accplan.html). All these models have been developed into software packages accessed through a graphic user interface (GUI) and designed to be easy to use. A critical limitation of these models is, however. that access to health care is defined to the 'nearest facility' a concept in which patients are often assumed to have access to or use the facility closest to them. No allowance is made for actual use of services and competition of facilities of different drawing power through the use of empirical data. Furthermore, an accuracy test to determine whether models predict well for the access and use health services in the pilot countries has not been carried out.

Even where distance is defined appropriately, the problem of transportation arises, such as whether a person used a car, the availability and cost of public transport and the condition of roads. This represents the total effort in travelling from origin to destination, and travel time has often been used as a measure of effort. With time, the sophistication of methods of measuring accessibility to health care improved from the use of straight-line distances to the incorporation of transport networks, and later the modelling of travel times. Martin *et al.* (2002) made use of comprehensive information on public transport systems, which showed in detail the travel time schedules of various transport companies in England, to develop an application which incorporated the modelling of both private and public transportation travel times for access to district general hospitals in Cornwall. The sophistication with which this can be done has greatly been influenced by the increase in both the skills and capacity to model spatial phenomenon. However, in SSA where the transport sector is loosely regulated, there are no comprehensive schedules of public transport and private vehicular ownership is low in rural settings, the value of incorporating transportation cost and vehicular travel speed is severely limited. In such instances, modelling for pedestrian travel may be the best way to achieve reliable estimates of physical access to health services.

In the next section, the origin and evolution of the discipline of spatial modelling are discussed. These are then related to increasing use of new spatial analytical and computing skills which have simplified the modelling of distance. This is followed by a section on the history and evolution of computer mapping, its impact on spatial modelling and its potential for public health.

1.7 Spatial modelling- history and evolution

In the 1960s geographers discovered that many simple statistical methods had important application in spatial pattern analysis (Birkin *et al.,* 1996). Following the publication in

1965 of *Location Analysis in Human Geography* (Haggett, 1965), techniques such as point pattern analysis, nearest neighbour analysis, correlation and regression established themselves an essential part of the geographer's methods of spatial analysis. With time the methods became more refined with the inclusion of multivariate models into the existing suite (Haining, 1993).

Concurrent with the development of spatial statistical methods was that of mathematical models particularly in the area of transportation and urban studies (Bertuglia *et al.*, 1994). This led to the derivation of a large number of spatial interaction models using entropy-maximising methods, an example of which were the gravity models (Wilson, 1967). However, in the 1970s there was a backlash against spatial modelling approaches, particularly their use in urban studies, and this was epitomised by the publication of the paper *Requiem of large scale models* (Lee, 1973). A key criticism was that the theories underpinning spatial modelling were 'simply wrong'. At the time, most of spatial modelling was driven by urban planners and it was argued that the models had failed to live up to expectation as evidenced by the worsening problems of urban areas. A consequence of this backlash was that the use of spatial models stalled until the emergence of Geographical Information Systems (GIS) and its subsequent complementarity with spatial modelling (Birkin *et al.*, 1996).

1.8 Geographical Information Systems (GIS) in health

1.8.1 The definitions of GIS

The term GIS was coined by Roger Tomlinson in the early 1960s for the government of Canada (Coppock & Rhind, 1991). GIS can be defined from three different perspectives; a tool-box, a database, or an organisation approach (Burrough & McDonnell, 2000). From the tool-box perspective, GIS is defined by Burrough (1986) as '*a powerful set of tools for collecting, storing, retrieving at will, transforming and displaying spatial data from the* *real world'*. Smith *et al.* (1987) gave a database definition of GIS as '*a database system in which most of the data are spatially indexed, and upon which a set of procedures operated in order to answer queries about spatial entities in the database'*. Cowen *et al.* (1988) gave an organisation-based definition '*as a decision support system involving the integration of spatially referenced data in a problem-solving environment'*.

More recently, the US Federal Geographic Data Committee (FGDC) defined GIS as '*computer systems for the input, storage, maintenance, management, retrieval, analysis, synthesis, and output of geographic or location-based information. In the most restrictive usage, GIS refer only to the hardware and software. In common usage (by organisations) they include hardware, software and data'*, (Richards *et al.*, 1999).

1.8.2 History of the development of GIS

Traditionally the use of GIS started in two fields: urban and regional planning (land use, traffic, transport planning etc) and construction and maintenance of utilities (electricity, water, etc) (Scholten & de Lepper, 1991; Openshaw, 1996). The development of the Canada Geographic Information System (CGIS) in 1963, which was established to analyse Canada's national land inventory, pioneered many aspects of GIS. This was followed by the development in the USA of the Harvard Laboratory for Computer Graphics and Spatial Analysis in 1964. This laboratory was an important research centre which pioneered the development of software for handling of spatial data. In 1966, SYMAP (Synagraphic Mapping System) was developed here as a pioneering automated computer mapping application. In 1969, Environmental Systems Research Institute (ESRI) was founded as the first commercial GIS software company. In 1971 the first LandSat satellite was launched heralding the exploration of the synergy between remote sensing and GIS. Global Positioning System (GPS) became operational in 1985 (GIS History Project: http//: www.geog.buffalo.edu/ncgia/gishist/). As the sophistication of spatial data capture and exploration increased, a debate began in the early 1990s on whether GIS is a tool or a science, with the latter gaining greater prominence among practitioners (Wright *et al.*, 1997). Many disciplines ranging from voting to fisheries have embraced the GIS revolution that peaked in the 1980s. In 2003, the US National Library of Medicine added the term 'Geographic Information Systems' to its controlled vocabulary thesaurus known as the MeSH (Medical Subject Headings), a step reflecting the importance and growing use of GIS in health and health care research (Boulos, 2004; http:// www.nlm.nih.gov/cgi).

Notwithstanding this large-scale interest, perhaps one area where GIS is least explored is in the health sector despite the recognition of the potential of GIS in health (Scholten & de Lepper, 1991; Loslier, 1994; Boelaert, 1998). A study on a cholera outbreak in London carried out by John Snow in 1854 is often cited to show the importance of spatial dynamics in the understanding of disease. John Snow demonstrated, using a simple street map, the striking relationship between cholera deaths and the supply of contaminated water from one company in the Soho area of London. More than a century later, Scholten & de Lepper (1991) and Loslier (1994) argue that since health is largely determined by environmental factors (socio-economic and physical) which vary in space, health will always have an important spatial dimension. Several reasons have been put forward to explain why the use of GIS in health was made such a slow progress. Twigg (1990) suggests that the nature and origin of GIS, which began in the physical and environmental sciences, gave these subjects a head-start relative to health research and the quality and nature of routine health data contributes to lack of GIS involvement. Success in the use of GIS, aside from expertise and computing resources, largely depends on the availability of spatially referenced data at the required spatial scale, criteria which routine health data in many countries fail to fulfil. Openshaw (1996) listed six generic principal impediments to the use of GIS in health research:

1. Organisational problems in the realisation or acceptance of the corporate nature of the technology and associated databases that often require management restructuring. This diminishes the impact of GIS or sometimes totally negates it at least in the short term.

2. Lack of access to necessary expertise, resources and information, either because lack of funds or acquiring copyright for information, or that the required is not available or in a useful format.

3. Lack of attention by GIS vendors to the development of applicable spatial analysis and modelling technologies for health as the principal markets were in the non-health sectors.

4. Absence of strong analytical tradition in areas where previously analysis was either impossible or impractical.

5. Fears of breach of data confidentiality or concerns about the misuse of personal health information.

6. Lack of demonstrated benefit which makes the initial applications difficult to establish.

1.8.3 Applications of GIS in public health: examples from high-income countries in the north

In spite of the well documented problems, the last decade has witnessed a rise in the application of GIS in public health and epidemiology (Hay *et al.*, 2000). Inevitably, the early applications of GIS in health were in the high-income countries, where the expertise was well established and resources were available to restructure health information systems to generate spatially referenced health data. These applications were both in the areas of public health planning (Andes & Davis, 1995; Kohli *et al.*, 1995; Bullen *et al.*, 1996; Grubesic, 2000) and mapping of disease risk and distribution (Dunn *et al.*, 1995; Wint *et al.*, 2002). As the application of GIS in public health and epidemiology increased, practitioners began developing GIS compatible information systems to make data integration simpler. For example, Nobre *et al.* (1997) developed an information system, GISEpi, designed for representation and elementary analysis of epidemiological data.

In Sweden, GIS was used to compute aerial or straight-line distances as a crude measure of geographic accessibility to PHC facilities (Kohli *et al.,* 1995). The Swedish annual population registration records, the national property register and the local health authorities were the main data sources. Each individual was linked to the property centroid and distances between each centroid and the health facility location were computed to assign population to the nearest health facility. GIS capabilities have been used to identify a nested hierarchy of localities for PHC management in West Essex, England (Bullen *et al.,* 1996) based on nodes or focal points for service provision related to barriers to movement, administrative areas, journey to work, school and general practitioners (GPs). These analyses revealed clear geographical patterns of patient to GP allegiance.

In North America, Hewitt & Tinline (2004) used GIS to model spatial accessibility of cancer clinics in Ontario, Canada. This study was used to project a new site for a cancer clinic to improve overall accessibility in the Hamilton region of Ontario. Currently, some regions in Carlifornia, USA, are using large, multi-layered GIS patient care and room management system which incorporates digital hospital floor plans, work-flow analysis and patient data visualisation. The system assigns patients to rooms and monitors discharge processes (http//www.esri.com/news/releases/02_4qtr/downey-medical.htm).

1.8.4 Applications of GIS in South America

In South America, Perry & Gesler (2000) used GIS to assess physical access to PHC in the remote, hilly and impoverished region of Andean Bolivia. The result showed significant variation in physical access to PHC across three study sites in the region. The analysis resulted in the development of a model of health personnel distribution to maximise physical access. In Costa Rica, a study was carried out to assess equity in access to health care and its impact on health reforms using GIS. Traditional measurements of access based on the distance to the nearest health facility were used. From this a comprehensive index of accessibility resulting from aggregation of all facilities weighted by their size, proximity and characteristics of both the population and the facility was developed. Half of the population were found to be less than 1 km from an outpatient care facility and 5 km away from a hospital. In equity terms, 12-14% of the population were undeserved based on three indicators: having outpatient outlet within 3 km, hospital within 5 km and 0.2 doctor yearly hours per person. The study was used to pinpoint underserved areas where improved access would have the greatest impact (Rosero-Bixby, 2004).

1.8.5 Applications of GIS in Africa

In Africa, the application of GIS in health has been focused on mapping the distribution and control of vector borne diseases using climatic data. An early application of GIS in disease mapping was the UNICEF Guinea worm eradication programmes within the 18 country 'Guinea worm belt' of West Africa (http://www.who.int/entity/csr/mapping). In Tunisia GIS has been used to investigate the spatio-temporal dynamics of zoonotic cutaneous leishmaniasis by a programme run by the Pasteur Institute and the Tunisian Department of Public Health (Mbarki *et al.*, 1995). Robinson (1998) used GIS to prioritise areas for tsetse and trypanosomiasis control in Zambia, where the emphasis has changed from widespread eradication to smaller-scale, community-based interventions. Digital maps of land tenure, percentage agriculture, stocking rates and relative arable potential were combined within a GIS to identify areas where trypanosomiasis was a direct constraint to agricultural development and where the presence of tsetse prevents access to areas adjacent to those under high pressure from livestock and agriculture. An atlas of human helminth infection in SSA has been developed under a WHO initiative with the aim of providing tools for targeted control. Presently work is been done with the two-fold objective of describing the prevalence of schistosome and intestinal nematodes and highlighting areas for which further information is required at the district level or its equivalent for the whole world (Brooker *et al.*, 2000; de Silva, 2003).

In recognition of the need to map endemicity and better define malaria risk in Africa, the Mapping Malaria Risk in Africa (MARA) project was founded as a collaboration of five African regions: Southern, Eastern, Central, Anglophone West and Francophone West (Snow *et al.,* 1996; http://www.mara.org.za). MARA has developed the first continental-level map of malaria transmission (Craig *et al.,* 1999) and the first evidence-based burden of malaria estimates (Snow *et al.,* 1999; 2003). It has also been at the forefront of developing geographical models of malaria using eco-physiological, climate and GIS data. In East Africa, GIS has been used to develop new operational systems for early warning and detection of malaria (Cox *et al.,* 1999).

1.8.6 Applications of GIS in SSA for health system planning

There has been little use of GIS in public health resource planning in Africa. Of the few public health-resource applications, most have been in South Africa. Zwarenstein *et al.* (1991) compared the often used population-per-bed ratios with a GIS method to investigate open access to private and formerly white-only hospital services in the province of Kwa-Zulu Natal. Catchment areas for hospitals were generated and access to services quantified. While the population-per-bed ratios suggested that hospital bed resources were racially unequal but adequate nonetheless, the GIS method revealed the widespread inadequacies in the allocation of hospital beds, worse for black communities in the province of Kwazulu/Natal.

Vector based GIS have been used to assess health service utilisation and placement and to create village level spatial databases for monitoring service utilisation (Le Sueur *et al.,* 1997; Booman *et al.,* 2000). The South African Ministry of Health/Medical Research Council's Malaria Information Systems (MIS) department have over the years developed and maintained a spatial database of shops, schools, clinics and family units in the rural areas of the province. Apart from active malaria surveillance data since 1976, the database also includes information on actual school and clinic attendance for every family collected during twice yearly home visits. Using these data, actual catchment populations were plotted and the information used to develop models based on distance for clinic placement that ensure the most effective utilisation of health services for the treatment of malaria.

Tanser (1999) used GIS to study PHC usage patterns and the implications of community based treatment of tuberculosis (TB) using the Directly Observed Treatment strategy (DOTs) in Hlabisa district, Kwazulu/Natal province and the relationship between distance to roads and HIV prevalence. Mapping TB supervision points before and after the expansion of the programme demonstrated how reducing the mean distance from homestead to treatment points improved access and use of services. In the same district, Tanser *et al.,* (2001) mapped 23,000 homesteads and using GIS spatially analysed usage patterns of health facilities. The study showed that 87% of the population used the nearest health facility; within an average distance of 4.7 km.

Elsewhere, the Tanzania Essential Health Interventions Project (TEHIP) has begun to look at the impact of poverty and income levels on the health status of the population within a spatially linked Demographic Surveillance Systems (DSS) (de Savigny *et al.,* 2001). Studies of health status and quintiles of income/poverty have revealed that the upper income quintile group lived nearer to health facilities than the lower income quintile groups. In Kenya no notable health service studies have been conducted using GIS. The only health application of GIS in Kenya has been the development of malaria risk models using climate and non-climate factors (Hay *et al.,* 1998; Snow *et al.,* 1998; Omumbo *et al.,* 2002; 2004; 2005).

In SSA countries, the potential of GIS in public health applications has not been fully utilised. Limited resources and lack of the necessary technical skills has disadvantaged heath care planners. Simple tools that would assist in multi-criteria evaluation and decision support would ease their task considerably and help target limited resources appropriately. It is with this in mind that a joint programme involving the WHO and UNICEF, HealthMap, was initiated in 1994 under the WHO-PHMP (http://www.who.int/csr/mapping/mappinginwho/en/). HealthMap was set up with the aim of providing support to public health programmes and encouraging an inter-sectoral approach to health management. HealthMap have introduced a GIS based information management system, the HealthMapper, in the framework of the Guinea worm control programme in West Africa. The HealthMapper is a surveillance and mapping application that aims to address key information needs across infectious disease programmes at national and global levels. The HealthMapper has user-friendly data management and mapping system which facilitates standardisation, collection and updating of public health data on epidemiology and interventions. It also provides immediate visualisation of data in the form of maps, tables and charts. Other than the Guinea Worm programme, there have been few examples of its application in other regional disease control programmes and no documented or reported use in the broader health sector planning.

1.9 Purpose, scope and outline of thesis

The development agenda in Kenya, like other low-income countries, is driven largely by the MDGs (Section 1.2). The progress and attainment of the MDGs in turn depend on good population health, which further relies on an adequately performing health system (Section 1.3). The failure of the health system to equitably deliver appropriate preventive and health interventions has been seen as major constraint in the achievement of the MDGs. An important indicator of equity in health care is the level of the population's access to and utilisation of health care (Section 1.4). Several factors influence whether people have access to health services, and if they do, whether they use them to better their health (Section 1.5). As previously discussed, these factors are broadly categorised into aspatial and spatial and it is the former that have received the greater amount of attention in the published literature (Section 1.5.2). However, there is still an abundance of published evidence that spatial factors, such as distance, play an important role in access to and use of health services. In several studies in SSA and other low-income countries distance has been shown to influence whether or not people use health services and has a positive correlation with mortality in many settings (Section 1.5.3). Knowledge of the population's level of distance-related access to health care, therefore, is critical to measurement of development goals. Nevertheless, the current methods used to measure distance to health services have a number of limitations, although significant improvements have been achieved through use of GIS (Section 1.6 & 1.8).

Even more recent attempts to improve the way distance is defined and spatial access models are developed have critical limitations, such as the assumption that people always use the facility nearest to them and that within a facility's service area the rate of utilisation does not vary (Black *et al.*, 2004). In addition, these models do not account for the competition between health facilities of different types. Moreover, most of the efforts in the use of GIS in public health are concentrated in the north with little published work in SSA, and none in Kenya (Section 1.8). In such an environment, the ability to measure health service access targets as defined for the development goals and improve resource allocation decisions for poverty reduction is severely compromised. It is against this backdrop that this thesis was conceptualised and related studies designed.

1.9.1 Scope and objectives of the thesis

1.9.1.1 General objective

To develop a spatial accessibility model of government formal public health service providers in Kenya.

1.9.1.2 Specific objectives

There are three specific objectives of this study:

1. Explore the validity and limitations of existing methods of modelling spatial accessibility of health services
2. Develop theoretical spatial access models against service use data provided through observational studies of formal GoK out-patient services and community surveys of paediatric fevers to identify best-fit models based on the incorporation into the theoretical models, the effects of service use in the presence of alternative providers of fever management services.
3. Explore the application of the best-fit accessibility model in defining health equity in Kenya by scaling it up to the national level

1.9.2 Thesis outline

Chapter 2 of this thesis explores the level of potential access to Government of Kenya-Ministry of Health (GoK-MoH) health services using straight-line or Euclidean distances. A background of the study districts is given. These are followed by the sources and types of data generated by the thesis. A detailed summary of the data by district is then given. Finally, a description of the analytical process and results of defining access using Euclidean distances are presented.

In Chapter 3[2] the spatial analysis of formal Government service providers in a GIS is used to investigate two broad issues; a) determining the role of distance in health service access and use; and b) assessing the method used to define health facility catchments. The reasons behind the choice of paediatric febrile patients and their use of GoK-MoH health services as a tracer for the broader access to and use of health services are given. In the first analytical part of the chapter the GIS is used to define the differences between theoretical straight-line (Euclidean) distance criteria for potential health service use developed in

[2] Digest of work described has already been published in: Noor, A.M., Zurovac, D., Hay, S.I., Ochola, S.A., Snow, R.W. (2003). Defining equity in physical access to clinical services using geographical information systems as part of malaria planning and monitoring in Kenya. *Tropical Medicine & International Health*, **8**: 917-926.

Chapter 2 and the Euclidean distances travelled by paediatric patients seeking malaria/fever case-management surveyed in the four study districts. In the second part of the chapter the suitability of accessibility modelling techniques used to define health facility catchments is assessed. The assumption underlying the access and utilisation models at this stage, that people always use the nearest health facility or that use is homogenous within a facility's catchment area are assessed. A series of new spatial analytical methods by which the validity of these assumptions are directly tested using the actual utilisation data of paediatric fever patients are presented.

In Chapter 4, high-resolution spatial and community household survey data for the four study districts are used to develop definitive models of GoK-MoH health service access and utilisation. The development of the spatial data and the community survey used to develop the access and utilisation models are described. Theoretical spatial models of access to GoK-MoH health services based on four different definitions of distance are presented, one of which is the Euclidean distance model developed in Chapter 2. This is then followed by a spatial analysis of patient choice patterns between any two neighbouring health facilities, resulting in the development of choice probabilities (boundary adjustment factors) for different service types. These choice probabilities are then used to adjust the theoretical models to account for patient's actual use characteristics. An accuracy assessment of both the calibrated and theoretical models is undertaken to test the reliability of the models and the impact of both the different definitions of distance and the use of adjustment factors. The best-fit model is then selected as the definitive access and use model of GoK-MoH health facilities. Finally, utilisation rate of GoK-MoH health facilities for the treatment of paediatric fevers, based on the best-fit model, is computed.

The realisation of the full benefits of the model developed in Chapter 4 depends on scaling it up to the national level, which in turn requires national-level spatial data at relevant resolutions. Chapter 5[3] describes how it is possible to construct a national database of health service providers from a diverse and disparate series of data sources. The chapter further illustrates how likely a re-constructed health provider database is to reflect reality and how feasible and accurate it is to provide a spatial dimension to enable this database to be used within a GIS system. In addition, a description of a national population, transportation, drainage and gazetted areas database is given. The utility of the national health services and other data in scaling up the access and utilisation models developed in Chapter 4 to the national level to define inequities in health service coverage and its value in modelling access is explored.

In Chapter 6 a conclusion of the main processes and outcome of this thesis is given. The policy implications of access models in defining equity in spatial access are also discussed. The future potential of the access model, particularly when used with vulnerability measures such as poverty and burden of disease is described. Finally, the limitations of the modelling approach developed in this thesis are discussed. The organogram presented in Figure 1.5 shows the type of questions each chapter tackles, the data used and the processes involved.

The data used in the thesis comes from a variety of sources. I designed the health facility survey tool, mapped and collected all health service data for the four study districts used in Chapter 2 first, and subsequently in Chapter 3 & 4. The health facility survey used in Chapter 3 were supervised, collected and refined by my colleague at the KEMRI/Wellcome Trust, Dejan Zurovac (Zurovac *et al.*, 2004). The community household survey used in Chapter 4 was a concerted effort by the KEMRI/Wellcome Trust

[3] A digest of the development of national database of health services has already been published in: Noor, A.M., Gikandi, P.W., Hay, S.I., Muga, R.O., Snow, R.W. (2004). Creating spatially defined databases for equitable health service planning in resource poor countries: the example of Kenya. *Acta Tropica*, **91**: 239-251.

team in Nairobi (of which I am part). My responsibility in both the health facility and community survey were to develop the spatial questions and supervise and refine the demographic, longitude and latitude and service use data. The retail audit data was obtained from a commercial company and further refined by myself and my colleague Abdinasir Amin (Amin *et al.,* 2003). The road, rivers and other water-bodies, elevation and gazetted areas data were obtained in electronic or paper copies from a variety of sources and institutions outside the KEMRI/Wellcome Trust. The enumeration area (EA) level population data for the study districts used in Chapters 2, 3 & 4 were obtained from the Central Bureau of Statistics (CBS). The national data on health services were obtained from an eclectic mix of sources as described in Chapter 5. The national population data was obtained from Dr. Simon Hay's population project in which I made a significant contribution. The thesis is largely an analytical study and all the spatial modelling, statistical analysis and interpretation were entirely my responsibility.

Figure 1.5 An organogram of the thesis outline

	Question	Data
Chapter 2	-What is the level of theoretical access to GoK-MoH health services if Euclidean distances were used to define physical access ?	-Spatial data of GoK-MoH health services -Spatial data of EA population distribution
Chapter 3	-Using Euclidean distances, what is difference between predicted use and actual use? -Do people always use the nearest health facility? -Is utilisation rate constant within a facility's catchment?	-Euclidean access map from Chapter 2 -Spatial patients' data from GoK-MoH health facility survey linked to the EA --Spatial data of EA population distribution
Chapter 4	-What are the differences between Euclidean, transport network, elevation & other barriers theoretical access models? -How does use between facilities of different types differ? -Can theoretical models be adjusted for actual use? -What is the difference between the adjusted and unadjusted model? - Which is the best-fit model?	-Euclidean access map from Chapter 2 -Transport network, rivers, elevation, lakes, swamps maps -Community household service use Data (spatially referenced)
Chapter 5	-What are the existing national data for scaling-up the best-fit access model? -How have they been developed? -Can they be used to scale-up the access model nationally? -What are the implications?	-National health service data -National transport network data -National elevation, rivers & other waterbodies, gazetted areas data -Modelled national population data
Chapter 6	-What is the potential of access model? -What are the limitations? -How can they be resolved? -What are the implications for MDGs?	

CHAPTER 2:
Background, materials, methods and preliminary analysis of access to health services

2.1 Introduction

The main objective of this thesis is to define the spatial determinants and develop models of access to and utilisation of GoK-MoH health services. The outcome of any disease is influenced by delay in decisions to seek care, timely arrival at appropriate diagnostic and treatment services, and the receipt of adequate care from service providers. Distance continues to limit access to more sophisticated diagnostics and ranges of treatments operated by formal health services. In Africa where the density of services to population distribution is low, distance becomes an increasingly significant influence upon access and use of services (Section 1.5.3.3).

Analysis of the percentage of population with access to health services has been a popular yardstick for development agencies to highlight the inequities between low-income and high-income countries in their basic needs for improved health (Section 1.5). This indicator of coverage is often computed as the percentage of the population that can reach appropriate local health services in no more than an hour (time required to walk about 5 km) (WHO, 1996b; World Bank, 2001; UNDP, 2003). In Kenya, the health sector reform strategy has set a target that everyone will be within 5 km of a health facility by 2010 (Section 2.2.4). Often, only a general national proportion is given, based on methods such as straight-line distances or self-reported travel times, whose limitations have been discussed in Section 1.5 & 1.6. Better ways of defining the influence of distance on access and use of health services need to be developed. Before this is done, the estimates derived from the use of straight-line (Euclidean) distances for four districts need to be known to enable comparison with the more sophisticated models that will be developed in subsequent chapters.

This chapter begins with the description of the Kenya context, with regards to its geography, the development of the health system, health reforms and the current service delivery structure (Section 2.2.3). Also in this section are the current health goals in Kenya and its efforts and progress in the attainment of the MDGs. In Section 2.3, the selection and the background of the study sites are discussed. This is then followed by a description of the development, sources and types of spatial data generated by the thesis, not only those relevant to this chapter but also to subsequent ones (Section 2.4). Finally, the process of developing theoretical (potential) spatial access maps using only the location of health facilities and population, based on Euclidean (straight-line) distances, are described (Section 2.5). The results of this analysis are presented (Section 2.6) and their implications for access to GoK-MoH health services in the four study districts and analysis in subsequent chapters are discussed (Section 2.7).

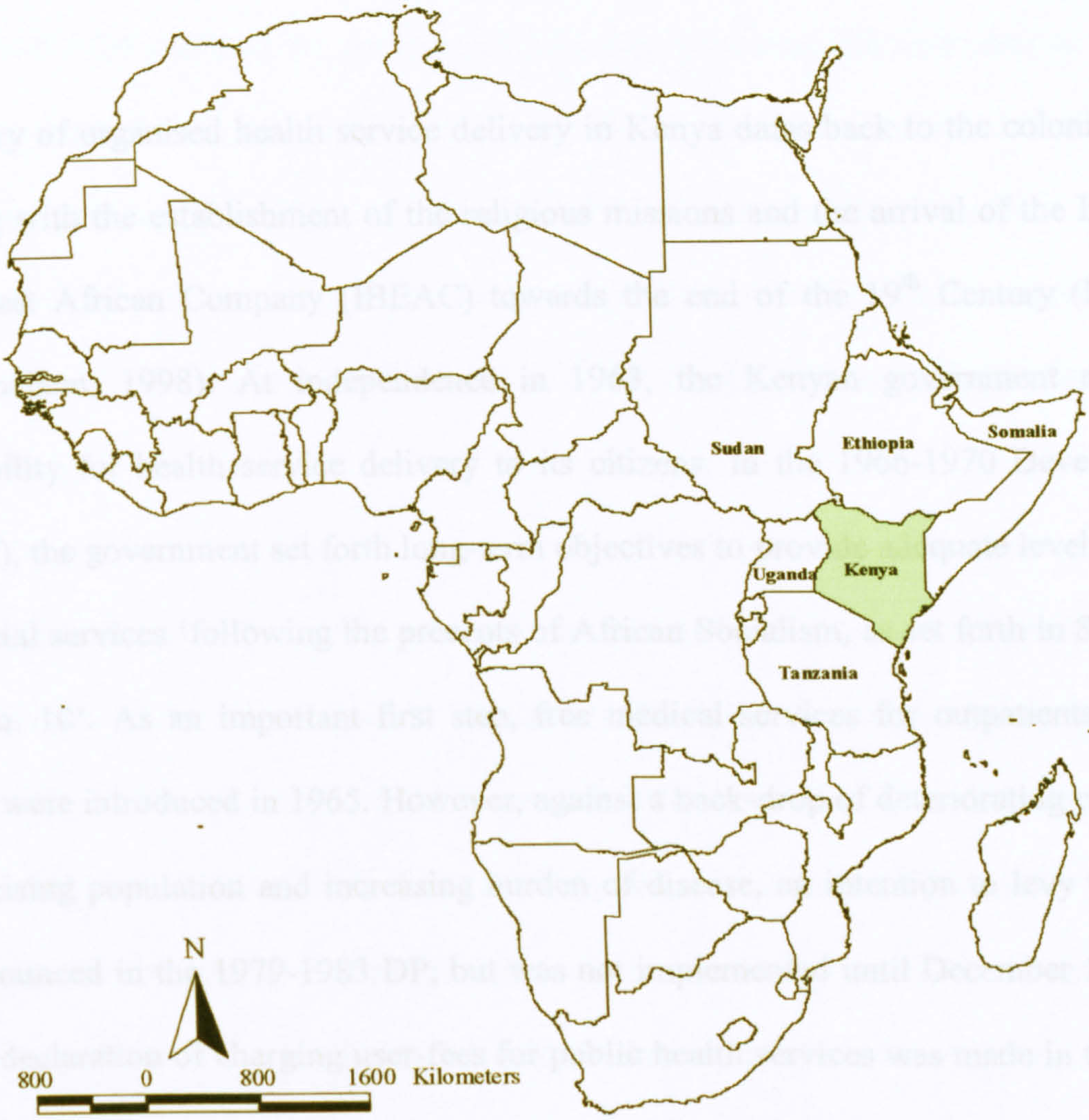
2.2 The Kenya Context

2.2.1 Geography

Kenya is located in East Africa and shares borders with Uganda to the west, Tanzania to the south, Ethiopia to the north, Sudan to the northwest and Somalia to the east. Kenya is also bordered to the south-east by the Indian Ocean where the port of Mombasa is located. Mombasa is the second largest city in Kenya (after the capital Nairobi) and is an important gateway for trade in Kenya and the landlocked countries in the Great Lakes region to the west (Figure 2.1). The country lies approximately between latitudes 5°00'N and 4°40'S; and between longitudes 33°83'E and 41°76'E. Kenya is approximately 580,367 km^2 in area (Ojany & Ogendo, 1988).

The country is divided into five administrative levels for purposes of local government, resource allocation (including education and health) and population census. There are eight provinces (first-level), which are further sub-divided into 70 districts (second-level). Districts are further sub-divided into divisions, locations, and sub-locations (third, fourth and fifth-level, respectively).

Figure 2.1 Map of Africa showing the location of Kenya and neighbouring countries



2.2.2 The development of Kenya's health care system

In Kenya attempts have been made to create an equitable health care system since independence in 1963. It was clear that access to health services was a major problem to the majority of the population of whom 95% were listed as rural in the 1962 census. Over the last 40 years several problems including a high rate of population growth, a seemingly unbridgeable regional disparity in health services, lack of qualified health and medical personnel and lack of reliable demographic, physical and socio-economic data, have impeded efforts to restructure the national health system (Mburu, 1980). These have been attributed to a combination of factors including the pervasive disaster resulting from the spread of HIV, increasing burden of disease posed by malaria and a declining access and quality of service provision (Owino, 1997; NCPD, 2003).

The history of organised health service delivery in Kenya dates back to the colonial days beginning with the establishment of the religious missions and the arrival of the Imperial British East African Company (IBEAC) towards the end of the 19th Century (Mwabu, 1995; Chaiken, 1998). At independence in 1963, the Kenyan government assumed responsibility for health service delivery to its citizens. In the 1966-1970 Development Plan (DP), the government set forth long-term objectives to provide adequate levels of free basic social services 'following the precepts of African Socialism, as set forth in Sessional Paper No. 10'. As an important first step, free medical services for outpatients and all children were introduced in 1965. However, against a back-drop of deteriorating economy, rapidly rising population and increasing burden of disease, an intention to levy user-fees was announced in the 1979-1983 DP, but was not implemented until December 1989. An explicit declaration of charging user-fees for public health services was made in the 1983-1988 DP. In the 1989-1993 DP, the government reiterated the decision to charge for public health services but changed the semantics of its position from that of 'charging user-fees' to that of 'introducing cost-sharing' to make it more acceptable to a public resistant to the idea (Mwabu, 1995).

The intention to decentralise health care delivery was first announced in the 1966-1970 DP but its implementation only started in earnest in 1970s with an aim of achieving health equity (Oyaya & Rifkin, 2003). Further, a decision was made to transfer health service provision from county and municipal councils to the central government. In an attempt at further decentralisation, the government announced, in the 1974-1978 DP, the establishment of 'rural health units' throughout the country. A rural health unit (or a dispensary) was meant to serve 50,000-100,000 people with a health centre as the focal point.

The 1966-1970 DP outlined the government's intentions to establish an insurance scheme for persons with formal employment. As a result, the National Health Insurance Fund (NHIF) was established in 1966. Initially, the NHIF paid for medical care received from private providers, and this created problems when charges were introduced at government facilities. The NHIF was later restructured to allow for government hospitals to be paid from the fund.

In the 1990s there was a further shift towards institutional and structural reforms following the publication of the World Bank's World Development Report: 'Investing in Health' (World Bank, 1993). Modelled on this report, the Ministry of Health published the 1994 Kenya Health Policy Framework (KHPF). This policy framework presented a series of situational analyses highlighting the problems faced by the Kenyan health sector, set out strategies to address these problems and defined what it referred to as 'the horizon of the government's health policies into the next century' (MoH, 1994). The KHPF articulates that the overall goal of the Kenyan health sector policy until the year 2010 as: '*to promote and improve the health status of all Kenyans through the deliberate restructuring of the health sector to make all health services more effective, accessible and affordable*'.

Recently, as part of overall strategy to meet the MDGs health targets, a Sessional Paper (Sessional Paper No. 2 of 2004) and a bill (The National Social Health Insurance Fund Bill, 2004), which seek to reintroduce access to free health care in Kenya, were published by the government (GoK, 2004) on May 28th 2004. The bill was passed by parliament in December 2004, but is yet to receive presidential assent (http://www.nationmedia.com, accessed 14/12/04).

2.2.3 *Kenya's health service decision-making and delivery structure*

Kenya's present health system decision-making structure is organised in four broad tiers (Oyaya & Rifkin, 2003). At the national level there is the Central Board of Health (CBH), followed at the provincial level by the Provincial Health Management Board (PHMB) and Provincial Health Management Team (PHMT). At the district level there is the District Health Management Team (DHMT) supported by various committees at the divisional and lower levels. Each of these levels requires health information of different types and resolutions in order to make health resource allocation decisions at that level.

Kenya's formal public GoK-MoH clinical services are structured at three administrative levels: central headquarters, provincial and district levels in a hierarchical system. Clinical services are provided by a number of partners including the GoK-MoH, missions, non-governmental organisations (NGOs), local authorities (LA) and the private-for-profit (MoH, 1994; GoK, 1998; MoH, 2002). Clinical facilities at district-levels are organised according to the types of services they provide. In an ascending order of service provision are dispensaries networked to sub-health centres and health centres through to rural health training centres, sub-district hospitals and district hospitals. Provincial general hospitals and the Kenyatta National Hospital (KNH) provide the major secondary and tertiary referral levels for the government health services. Dispensaries provide outpatient care only, without laboratory support. Health centres provide outpatient and limited 24-hour inpatient care, have laboratory support, and have no blood transfusion services available. A district hospital provides outpatient and inpatient care including blood transfusion services, and has laboratory support. A small number of sub-health centres and sub-district hospitals, as the inter-level health facilities, also exist. Since the service capacities of these levels of care, related to malaria case management, do not differ significantly from any of the above belonging to the three-tiered structure, for the purpose of this study, sub-health centres were classified with dispensaries and sub-district hospitals with health centres.

Nurses and clinical officers provide outpatient services to sick children in dispensaries and district hospitals respectively. In health centres, outpatient consultations are performed by both nurses and clinical officers. In addition, both at district and provincial levels, specialist hospitals, for example, for tuberculosis or leprosy, and maternity homes provide additional support.

2.2.4 Kenya's current health care development targets

The KHPF established a set of six goals: 1) equitable allocation of government resources to reduce disparities in health status; 2) increasing cost-effectiveness and cost-efficiency of resource allocation; 3) continued management of population growth; 4) enhancing the regulatory role of government in all aspects of health care provision; 5) creating an enabling environment for increased private sector and community involvement in health service provision and finance; and 6) increasing and diversification of per capita financial flows to the health sector. While most of the goals are strongly inter-linked, of particular importance to this thesis is the first goal; equitable allocation of government resources to reduce disparities in health status. Three broad strategies were laid out for achieving this goal:

1. Developing a combined epidemiological and micro-economic framework for health planning linked to analyses of health status and clear definition of types and scales of cost-effective interventions that will ensure nationwide, equitable access to essential curative as well as preventive services.

2. Development, adoption and use of standard criteria for geographic allocation of resource

3. Development, adoption and use of standard criteria for allocation of resources to individual health facilities

Due to the slow progress in the implementation of the 1994 KHPF, the 1999-2004 National Health Sector Strategic Plan (NHSSP) was developed in July 1999 (MoH, 1999). This document reemphasised the goals of the 1994 KHPF and set more explicit ways of pushing reform forward while taking stock of what had already been achieved. One of the shortcomings of the 1994 KHPF was the insufficient articulation and prioritisation of the strategies in addition to lack of costing of the plans to define the relevant health sector resource requirements. This resulted in the plans lacking commitment from some of the key stakeholders. The 1999-2004 NHSSP involved a greater numbers of key stakeholders in the process. Several generic indicators for monitoring and evaluation of the health sector reforms were developed. Of particular importance was the definition of indicators of access to health services that were divided into physical and economic. The physical indicators of access were: proportion of rural population residing within 5 km of a health a facility with full package of basic health services, pharmacy, vendor or drug store; proportion of health facilities equipped with communication equipment; population per doctor/clinical officer/nurse/hospital bed. However, there were no clear methodologies defined in the reform strategy for measuring these indicators. Furthermore, the relevant data required are not available nor are there any tangible efforts on the MoH's side to collect them. In addition, the appropriateness of these indicators as measures of health system performance has not been presented with any empirical evidence.

2.2.5 Kenya's efforts and progress in attaining the MDGs

The first MDGs progress report for Kenya was prepared by the Government and a UN country team in 2003 through a national stakeholder process convened by the PRSP Secretariat (GoK-UNDP, 2003). The report began by reiterating the government's commitments to MDGs, revitalising the economy and streamlining financial systems in the spirit the Economic Recovery Strategy for Wealth and Employment Creation (ERSWEC). The key socio-economic indicators at the time of publication of the report are given in Table 2.1.

Table 2.1 Key socio-economic indicators in Kenya based on projected population of 31 million in 2002 (Source: GoK-UNDP, 2003)

Indicator	Value	Year
Population size (M)	28.7	1999
Population growth rate (%)	2.9	1999
Life expectancy at birth (yrs)	46.4	2003
GNP per capita (US $)	1.022	2000
Human Development Index (value)	0.489	2001
Human Development Index (rank)	146	2001
Population below poverty line (%)	56	1997
Prevalence of HIV/AIDS in adult population aged 15-49 (%)	10.1	2002
Population without access to drinking water supply (%)	55	2000
Proportion underweight under-five children (%)	32.5	1999
Adult literacy rate (%)	83	2003
Net enrolment rate in primary education (%)	73.3	2000
Ratio of girls to boys in primary education (%)	74.8	2000
Under-five mortality rate (per 1,000 live births)	100	1999
Maternal mortality rate (per 100,000 live births)	590	1998

The most recent Kenya demographic and health survey (KDHS) showed that mortality rates have began to rise following a period of decline as shown in Table 2.2 (NCPD, 2003). Levels of under-five mortality were 114 deaths per 1000 while infant mortality rate was 78 in 1000 in 2003 and show a steady rise in rates since mid 1980s.

Table 2.2 Trends of early childhood mortality rates in Kenya, 1984-2002[a] (NCPD, 2003)

Survey year	Approximate calendar period	Infant mortality	Under-five mortality
1989	1984-1988	60	89
1993	1988-1992	62	96
1998	1993-1997	74	112
2003	1998-2002	78	114

a Data for 1989, 1993 and 1998 excluded several northern districts

On 18th January 2005, the Kenyan government launched the National MDGs with a call to development partners to assist Kenya implement the programme. In a statement, the government acknowledged that 'a casual look at the Needs Assessment Report (NAR) reveals that a huge amount of resources above what the country can raise is required' (The Standard, 18th January 2005). The NAR was developed as a vehicle upon which various sectoral interventions and associated costs to meet the MDGs will be based. The Government further revealed that Kenya had only made significant progress in education and the fight against the HIV/AIDS scourge. To enhance the delivery strategies of resources required for the MDGs targets, the Government has set up a Constituency Development Fund (CDF) in order for the benefits of the programme to reach grassroots levels. Other efforts designed to achieve the MDG goals are membership to the African Peer Review mechanism where member countries audit themselves, and the recently re-launched National Economic Social Council (NSEC) as a policy adjustment that targets improving the welfare of Kenyans.

2.2.6 Summary of Kenya's targets for access to health care

The main health care access targets for Kenya are documented in the health care reform strategy and the more recent MDGs. The health reform strategy requires that everyone will have access to a health facility with full package of basic health services to within 5 km by 2010 (MoH, 1999). A cornerstone to the attainment of the MDG health goals is access to effective preventive and curative measures for HIV/AIDS, malaria and TB. In addition, access to various obstetric services have been outlined to reign in maternal mortality (http://www.un.org/millennium). Although the health care reform strategy is clear on the importance of distance to health services as an indicator of access to health care, no explicit methodologies have been outlined to measure it. For the MDGs, the proportion of people of different age and gender categories with access to the relevant health care services and interventions is used as an indicator. The position of spatial dimension of health care is inherent in this indicator but not explicitly defined.

2.3 Background on the selection and characteristics of the study districts

The work presented in this thesis was integrated into studies that formed part of an ongoing collaboration between the Ministry of Health's (MoH) Division of Malaria Control (DOMC) and the KEMRI/Wellcome Trust Research Programme. This collaboration identified 4 study districts across Kenya, that form the basis of efforts by the MoH to monitor community use of services related to malaria control and prevention and health impact following renewed efforts to Roll Back Malaria. As such they were not explicitly selected for this thesis but are nonetheless considered sufficiently representative. These purposively sampled districts represent most of the varied malaria ecology of Kenya and reflect the diverse population, health and climatic conditions across the country. However, they are not representative of the highly urbanised districts (e.g. Nairobi and Mombasa) and the pastoralist communities in the north of the country and any attempt at generalise of the models should take this into consideration. The districts also fall within the poorest half and may not be representative of rich districts, particularly those in the richest quartile. The four purposively sampled districts are as shown in Figure 2.2. A description of the study districts follows.

Figure 2.2 Map of Kenya showing the study districts

2.3.1 Bondo

Bondo district is one of the twelve districts in Nyanza Province and lies between latitude 0.400^0 south to 0.050^0 north and from longitude 33.967^0 to 34.433^0 east. It was carved out of Siaya district in 1998. Along its western border lies Lake Victoria. Rainfall in the district is bimodal and average annual rainfall is 1,400 mm. The long rains occur between March and June with the peak periods being between April and May. The short rains occur between August and November. The district experiences intense, perennial malaria transmission.

The population are predominantly JaLuo (95%). The JaLuo belong to the Nilotic people originating from North Africa following the Nile during the 17th century (Cohen & Odhiambo, 1989). Villages typically comprise loose conglomerations of homesteads separated by garden plots, grazing land and streams. Subsistence agriculture, fishing and small business are the principal occupations of much of the district. The results of household incomes and expenditures undertaken during the national family Welfare Survey between June and July 1994 in 313 households of the then Siaya district showed that the mean monthly household income was about Kshs 5,500 while the mean monthly expenditure was about Kshs 5,000 of which Kshs 331 (6.6%) was spent on health (CBS, 1994). The most recent poverty report derived from a household survey conducted in 1997 by the CBS showed that 58% of people in Siaya district (of which Bondo was part) lived below the poverty line, and was ranked the 15th poorest district in Kenya (CBS, 2000)

2.3.2 Greater Kisii (Kisii Central & Gucha)

Former Kisii district was split in 1997 to form Kisii Central and Gucha districts. For the purposes of the site selection they are regarded as Greater Kisii in this thesis. The combined districts are located between 1200 and 2200 metres and as such constitute the typology of "highland" malaria. Malaria risks are acutely seasonal and vary in magnitude between years. Rainfall is characterised by long rains which occur from March to June and short rains from September to November. December and January are relatively dry months. The district lies between latitude 0.500^0 and 0.967^0 south and longitude 34.700^0 and 35.083^0 east.

The district is mostly hilly and receives an average rainfall of over 1500 mm per year. The hilly terrain poses problems for transportation. High population density has led to many primary forests being cleared for cultivation. Subsistence farming is the most widespread activity with relatively small farm holdings; ranging from 0.5 to 4.5 acres. The population are predominantly Kigusii. The results of household incomes and expenditures undertaken during the national family Welfare Survey between June and July 1994 in 362 households in 41 clusters of Greater Kisii district showed that the mean monthly household income was about Kshs 10,000 and mean monthly expenditure was about Kshs 8,000 of which Kshs 554 (7%) was spent on health (CBS, 1994). The most recent poverty report derived from a household survey conducted in 1997 by the CBS showed that 57% of people in the district lived below the poverty line. In the same period the district was ranked the 17th poorest district in Kenya (CBS, 2000)

2.3.3 Kwale

Kwale district, one of the seven districts in Coast province, is located in the southeastern corner of Kenya on the border with Tanzania. The district lies between latitudes 3.550° south and 4.667° south and longitudes 38.450° and 39.667° east. Kwale district is located along the Indian Ocean on the east and Republic of Tanzania to the south. Annual average rainfall varies from 900 mm to 1500 mm per annum along the coastal strip and 500-600 mm further inland. Malaria transmission is hyper- to holoendemic with seasonal distribution of risks associated with rainfall patterns. Major topographical features are the coastal plain extending 10 km inland, the foot plateau, the coastal uplands also known as the Shimba Hills, and the Nyika plateau within the hinterland. Subsistence farming is a common economic activity.

The majority of the population are of the Mijikenda ethnic group (80%). The Mijikenda are a Bantu community and the term Mijikenda refers to people belonging to "nine villages".

In Kwale the Wadigo and Waduruma are the main Mijikenda groups. Income and expenditures were assessed during a national sample survey between June and July 1994 among 191 households in 26 clusters of Kwale and the district had a mean monthly household income of about Kshs 15,000 and a mean monthly expenditure of about Kshs 10,000 of which Kshs 126 (1.3%) was spent on health (CBS, 1994). The most recent poverty report derived from a household survey conducted in 1997 by the CBS showed that 61% of people in Kwale district lived below the poverty line. This district was ranked the 14th poorest district in Kenya (CBS, 2000).

2.3.4 Makueni

Makueni district is one of the twelve districts of Eastern Province and lies between longitudes 37.144° and 38.517° east and latitudes 1.523° and 2.987° south. Rainfall is very limited and average annual rainfall is approximately 735 mm per annum. The long rains occur mainly in March to April and the shorter rains between November and December. The district has acute seasonal malaria transmission of low intensity with marked spatial heterogeneity owing to the district encompassing semi-arid areas toward Kitui district and more fertile areas closer to Nairobi. Crop farming in the district is mainly for subsistence purposes.

The majority of the population belong to the Bantu group of WaKamba (97%). The results of household incomes and expenditures undertaken during the national family Welfare Survey between June and July 1994 in 175 households in 19 clusters of Makueni district showed that the mean monthly household income was about Kshs 5,500 while the mean monthly expenditure was about Kshs 5,000 of which Kshs 161 (3%) was spent on health (CBS, 1994). With 74% households classified as living below the poverty line, Makueni ranked second poorest in the country after Homa Bay District in Nyanza Province (CBS, 2000).

2.4 Methods

2.4.1 Developing the GIS layer of population distribution within the study districts

The most recent population and housing census of Kenya, was conducted on 24/25th August 1999 (CBS, 2001a). The population census enumeration adopted a *de facto* approach whereby everybody within the country was enumerated according to where they were resident on the census night (CBS, 2001a). During the census, information on the spatial distribution and number of households, structure (age and sex), educational level, fertility, mortality and migration rates, urbanisation, size and utilisation of labour force, housing and availability of social amenities were collected (CBS, 2001a; 2001b). Kenya's administrative hierarchy is divided into five levels (province, district, division, location and sublocation) (CBS, 2001a). The highest spatial resolution population data readily accessible in the public domain are provided at the sub-location. This fifth-level administrative unit is defined by an average population of about 4,250 people and an area of 88.3 km^2.

In collaboration with the CBS, population totals recorded at enumeration area (EA) level (the smallest census unit), were obtained for the four study districts. Each EA comprises part of a village, a whole village or group of villages that are usually not more than 100 households (circa 500 people). The EAs were classified into urban and rural based on expert opinion. Areas with an estimated population of 2,000 people or more, a significant amount of commercial activity and well connected to the motorable transport networks were classified urban, the rest as rural (David Nalo, Personal Communication). These EA maps were created through field traverse surveys of the entire country at the village level over the period 1996-1999 and were manually drafted by CBS cartographers. The aim of delineating the EA boundaries was to determine an area that could be fully enumerated by a single enumerator on the census night, to avoid duplications and omissions and to mark locations of structures earmarked for call-backs (CBS, 2001a). The EA maps used during the national census were digitised using ARCINFO (PC version 3.5, ESRI Inc., USA) and MicroStation 95 (Bentley Systems Inc., USA).

A number of errors were identified at this stage of the project. These included lack of correspondence between the sub-location boundaries derived from the EA maps and the sub-location maps from the main national fifth-level digital national administrative map. These were reconciled and corrected digitally. A second, more serious problem was a projection error in the main fifth-level national administrative boundary map supplied by the CBS. Although the CBS provided details of an inherent X-axis shift in the map of 668 km or about 1 Universal Transverse Mercator (UTM) zone, there still remained a distortion even when this shift was accounted for. This was noticeable because the map did not fit well with the Kenya maps of correct projection such as the Africover (URL: http://www.africover.org) and the United Nations Second Administrative Level Boundary (UN-SALB) maps (www3.who.int/whosis/gis/salb/salb_home.htm). In addition, when a map of health facilities positioned through GPS was overlaid, many of the health facilities did not fall in the correct locations on the map. A closer look at the map showed that the problem was most serious in the Coast and North Eastern provinces.

At this stage, the CBS were requested to provide the sub-location maps separate for each of the eight provinces as they were prior to merging of the maps to make a composite national map of sub-locations. These maps were in a UTM projection. Further investigation revealed that the CBS used Clarke 1866 as the projection ellipsoid and a central meridian (CM) of 33 degrees instead of the more commonly used ellipsoid Clarke 1880 and a CM of 37 degrees. In addition, it was noticed that Coast and North Eastern provinces were digitised with a different type of a shift. When all the province maps were merged, there was an overlap between the boundaries of these two and the other six provinces. This overlap was not appropriately resolved; instead the boundaries of the two provinces were coerced to fit with the rest of the maps by erasing the overlaps. The result was a map with both a projection and a shift error and in which the erased polygons of the Coast and North Eastern provinces were smaller than they should have been. These were then resolved by first projecting all provincial sub-location maps from UTM to geographic. Then the North Eastern (including Moyale district) and the Coast provinces were moved one at a time to fit with the external district boundaries of the Africover map using ShapeWarp 2.2 in ArcView GIS (Version 3.2, ESRI Inc., USA). All provincial sub-location maps were then merged resulting in minimal digitisation errors between the boundaries which were then manually corrected. Apart from the errors that were in the physical boundaries of the maps, there were significant errors in the corresponding attribute table. There were several spelling mistakes, wrong naming of polygons and duplicate identification numbers for discrete polygons. These were corrected using the population census book (CBS, 2001a). Further, unique identification numbers (IDs) were generated for each of the administrative levels (province, district, division, location and sub-location) and EAs. Sub-location and EA level attribute data for the population were exported into ArcView 3.2 (ESRI Inc., USA) and linked to the respective map using the unique IDs.

2.4.2 Developing the GIS layer of formal health services within the study districts

Preliminary health facility databases and maps were first developed as described later in Section 5.2.1. These were then taken to the districts in March-April 2001 (Greater Kisii), June 2001 (Bondo), June-July 2001 (Makueni) and August-September 2001 (Kwale). The District Health Management Teams (DHMT) were contacted to identify omissions, replications and errors of all Government and Mission facilities. Enquiries were also made about private health facilities from the DHMT and cross-checked with other knowledgeable people in the district to ensure that those not reported by DHMT were detected. Finally each facility was visited to complete a simple questionnaire on its address, status, personnel and services provided and to record a longitude and latitude [Appendix 1]. Coordinates were recorded using a hand-held geographical positioning system (GPS) receivers (Garmin *etrex* (Garmin Ltd., Kansas, US) and Trimble (Trimble Navigation Ltd., California, US). To minimise recording errors three longitudes and three latitude readings were taken for each facility and the average reading used to position the facility. The assumed accuracy was +/-15m (URL: http://www.garmin.com) for the periods when the GPS readings were taken.

Data entry was done using MS Excel 1997 (Microsoft Corporation, Seattle, Washington, USA). Each health facility was assigned a unique number which was then used for all subsequent reference to that facility. Codes to identify the type of facility and the health care provider or agency were also generated (Table 2.3).

Table 2.3 Codes for different health care providers and types of health facilities

	CODE
HEALTH CARE PROVIDER	
Ministry of Health	MoH
Local Authority	LA
Armed Forces	AF
Other Ministries	OM
Mission	MISS
Non-Governmental Organisation	NGO
Private	PRIV
FACILITY TYPE	
District and sub-district hospital (MoH, MISS, NGO)	1
National and provincial hospital	2
Health and sub-health centres	3
Dispensary	4
Private hospital	5
Private clinics	6
Maternity and nursing homes	7
Specialist treatment hospitals	8
Institutional health facilities	9

2.4.3 Developing the GIS layer of informal health services within the study districts

A private commercial company, Research International East Africa Limited (RIEAL) carried out a retail census in 1999-2000 for all outlets in Kenya. The exercise involved mapping of the outlets using GPS. The country was divided into four regions; Nairobi, Eastern, Western and the Coast. A group of interviewers led by a supervisor were appointed for each region. Each group was made up of 13 sub-groups. Each sub-group consisted of 14 clerks and a team leader. All the groups began working in Nairobi and when this was done each group moved to its designate region. During a visit to the outlet the attendant was interviewed using a structured questionnaire. The questionnaire captured information on the type of outlet, the operating hours, the number of people that operate it and the type of items stocked including anti-malarials and anti-pyretics. In addition, information on the outlet's surrounding environment, the name of city, town or market centre it was located in, type of buildings and all brand signs that were unique to the outlet were obtained. The data were entered in MS Excel 97.

The retail outlets data for the four districts were purchased from RIEAL. For each district, those outlets that sold anti-malarials and anti-pyretics were selected from the larger database. Before these data were purchased a thorough check on their completeness, particularly the accuracy of the GPS coordinates, was undertaken. This was done by exporting the data to ArcView GIS (Version 3.2, ESRI Inc., USA) and superimposing them on district sub-locations maps. In all the four districts there was a lack of correspondence between the positions of the retail outlets and the sub-location maps of the district. This was identified as a two-fold problem; one was due to the way the co-ordinates of the outlets were entered and the other was due to an error in the actual positioning of the outlet. During the survey, the co-ordinates of the outlets were captured as degree-minutes-seconds (DMS) but were entered as decimal degrees (DD) without making the appropriate conversion. These co-ordinates were returned back to their DMS format and appropriately converted to DD format. Where there was an error in positioning, RIEAL physical addresses were compared against correct coordinates of market centres obtained from topographic maps, International Livestock Research Institute (ILRI) village data (Section 5.2.2), EA maps and GPS co-ordinates of market centres collected during the health facility mapping exercise. Positions of these outlets were then redefined to the market centre or EA.

All outlets selling anti-malarials and anti-pyretics were then assigned a unique five digit code; one for the district and four for the outlet. The CBS classification of urban and rural areas described in Section 2.4.1 was used to define "urban" or "rural" outlets. The outlets were further classified into pharmacies, large *dukas* and small *dukas*. The latter two categories were based on the number of people working in a retail outlet that was not a pharmacy (Amin *et al.,* 2004). All the shops were then assigned to the relevant division, location, sub-location and EA.

2.4.4 Developing maps of transportation networks for study districts

In the study districts, roads form the main, and in some cases, the only transport network used by communities to access health services. A most recent road network (0.040 km/km^2 for Kenya) was obtained from Africover (URL: http://www.africover.org) (Section 5.4). The road data were not properly classified into the different road classes in Kenya (all-weather and dry-weather roads, main tracks and footpaths). These data were used as the template for a roads layer which was then updated and classified from 1:50,000 topographic maps. In addition, more recent and appropriately classified road maps for Greater Kisii district were obtained from ILRI. Further, the road maps for the four study districts were improved by digitising additional roads from EA level maps obtained from the CBS.

The Nairobi-Mombasa railway traverses parts of Makueni and Kwale districts. A map of the railway line was obtained from DCW (Danko, 1992). In Bondo and Kwale, access to Mageta and Wasini Islands respectively is by use of navigable waterways. In the accessibility modelling described in Chapter 4, these islands were connected to the road network through the use of a segment representing the distance to the nearest point on the mainland. This segment was then considered to be the equivalent of a road.

2.4.5 Developing elevation maps

Slope plays an important part in determining access to health facilities. It is ordinarily easier to travel on flat land than on a hilly one. For example, if a road traversed a hilly terrain, it is bound to have a lower average travel speed compared to one on a flat land even when the road class is the same. In a hilly region like Greater Kisii district, the lowlands (valleys) between settled uplands (hills) act as obstacles to travel. To determine the influence of slope on accessibility to health services, a digital elevation model (DEM) was used (Section 4.3.2.3). A DEM for Kenya developed at ILRI from contours at 20 m intervals digitised from 1:50,000 topographic maps was acquired (Section 5.5). These contours were digitised using ARCINFO 3.5 (ESRI Inc., USA) and then exported to ArcView GIS (Version 3.2, ESRI Inc., USA). The contour map was raterised into a 20m DEM. For each of the four study districts a DEM was clipped from the national map (Figures 2.3 [A-D]). Any directional change in slope was assigned a weight reflecting its influence on movement as described in Section 4.3.2.3.

2.4.6 Developing maps of parks and forests

Due to legal restrictions, transport routes that pass through protected areas such as parks and forests are seldom used by the population to access health services. For instance, while a road passing through a park or a forest might have similar travel speeds as a road passing outside the park, their contribution to access to health services will differ because people do not freely use them. This difference needed to be quantified and used in running the access models. A digital map of all parks, game reserves and other sanctuaries in Kenya was obtained from the Kenya Wildlife Service (KWS) (Wycliffe Mutero, Personal Communication). The GIS section of the KWS produced these maps for efficient management of wildlife sanctuaries. A digital map of forest was obtained from the Africover (URL: http:\\www.africover.org). Many irregularities were found in the gazetted area polygons of Kenya and the details on how this were corrected and the present state of the gazetted areas map of Kenya are given in Section 5.5. Data specific to the study districts were abstracted from the respective national maps (Figures 2.3 [A-D]).

2.4.7 Rivers and other water bodies

Navigable waterways are not widely used as a means of transportation in most of the study districts. Rivers and other water-bodies, nonetheless, act as obstacles to movement since only a small proportion of the roads that traverse such features have bridges. Rivers and other water-bodies were abstracted from the Africover database (URL: http://www.africover.org) for Kenya. This was not of sufficient detail so the four study districts EA level maps which included details of rivers, swamps and lakes were used to update the Africover coverages. The rivers were classified into perennial and seasonal rivers or streams while the other water-bodies consisted of lakes and swamps (Figures 2.3 [A-D]).

2.5 Analysis of potential usage of health facilities

Thiessen polygon (TP) technique (ArcView 3.2, ESRI Inc., USA) was used to generate catchment areas for each GoK-MoH health facility in the four districts. This technique assigned each point on the map to the nearest health facility based on straight-line (Euclidean) distances, creating polygon maps of facility catchment areas. The EA-level population maps were rasterised such that population was distributed evenly within the EA at 100 m resolution. Using ArcView 3.2 GIS *geo-processor* extension, the population of all EAs falling within a facility's catchment area was summed and recorded as the *potential users* of that facility. In computing potential users, all facilities, regardless of the type or size were assumed to have the same geographic drawing power for the purpose of this study, since they all provide similar out-patient clinical services (Zurovac *et al.* 2002; 2004).

The number of people within 5 km of each GoK-MoH health facility was computed and were then added up to compute an aggregate value for each district. This threshold was selected because it is the one proposed in the Kenya health reform strategy as one of the indicators of health service coverage (MoH, 1999). Further, mean access distances were computed for urban and rural EA in each district. Each urban and rural EA was further stratified by type of nearest health facility and mean access distance was computed by facility type. These Euclidean access maps were then classified into three access-bands: 5 km; > 5-10 km; and > 10km to visually demonstrate the variation in access to GoK health services within and between districts.

2.6 Results of district level mapping and Euclidean distance measures

2.6.1 Summary of findings of district-level service and population mapping

In this section a summary of the principal characteristics of each district are presented to allow an understanding of the four districts in terms of their population density, topography and gross access to services. These summaries are presented in Tables 2.4-2.6 and Figures 2.3 [A-D].

In order of the highest to lowest 1999 census population were Greater Kisii, Makueni, Kwale and Bondo, although the latter had a higher population density than both Makueni and Kwale. The average population per EA was highest in Kwale and lowest in Bondo. Most of populations (84-97%) in the four districts were rural (Table 2.4). On average, a household in Bondo had 4 persons while the other three districts had an average of 5 persons.

The 1999 population census figures were projected to 2002 so that population data used in the analysis was that of the year when most of the surveys presented here were conducted. The equation $\mathbf{P}_{2002} = \mathbf{P}_{1999}\ e^{rt}$ was used in the projection of population, where P_{1999} was the 1999 population census and P_{2002} was the required 2002 population, t was the number of years between 1999 and 2002 and r was the average annual growth rate (Table 2.4; CBS, 2001a). The projected population for 2002 for was between 1.3% (Makueni) to 1.9% (Kwale) higher than the baseline 1999 census population. The ratio of health facilities, personnel, beds, microscopy and retail were computed using the 2002 projected population.

Makueni district had the highest number of health facilities (n=201) in all the three main sectors (MoH, Mission/NGO and private combined) while Bondo had the lowest (53). GoK-MoH public health sector accounted for 51% of all health facilities in Kwale, 40% in Bondo, 29% in Makueni and 24% in Greater Kisii. An analysis of the number of people per health facility using the 2002 projected population showed that overall; Makueni had the fewest people per health facility while Greater Kisii had the highest. The analysis of the GoK-MoH public sector health facilities only, showed that Kwale had the fewest number of people per health facility with Greater Kisii having the highest population per government health facility. Ratios of population per health worker, bed and microscope are shown in Table 2.5. The ratio of retail outlets to population was highest in Kwale and lowest in Greater Kisii.

The extent of the road network, water features and gazetted areas are presented in Table 2.6. Although the districts had a similar coverage of primary roads, the secondary roads network in Bondo and Greater Kisii were twice as high as that in Kwale and Makueni. The variation in elevation was the greatest in Makueni, followed by Greater Kisii and Kwale with the highest range and largest standard deviation compared to Bondo (Table 2.6).

Table 2.4 Demographic characteristics of the study districts

District	Area	Total Population 1999 (% rural)	Annual growth rate	Projected population 2002	Population density (people/km^2) (2002)	Number of EA 1999 (% rural)	Number of households 1999 (% rural)	Average number of people per EA in 1999
Bondo	960 km^2	238 780 (94)	0.0046	242 098	245	673 (95)	56,607 (93)	355
Greater Kisii	1,310 km^2	952 725 (92)	0.0046	965 963	737	1,975 (94)	190,091 (86)	482
Kwale	8,295 km^2	496 133 (89)	0.0062	505 447	61	822 (80)	92,594 (84)	604
Makueni	8,266 km^2	771 545 (97)	0.0042	781 327	95	1,766 (95)	144,320 (94)	437

Table 2.5 Health facilities, personnel, beds, microscopes, retail outlets and their ratio to 2002 projected population in the study districts

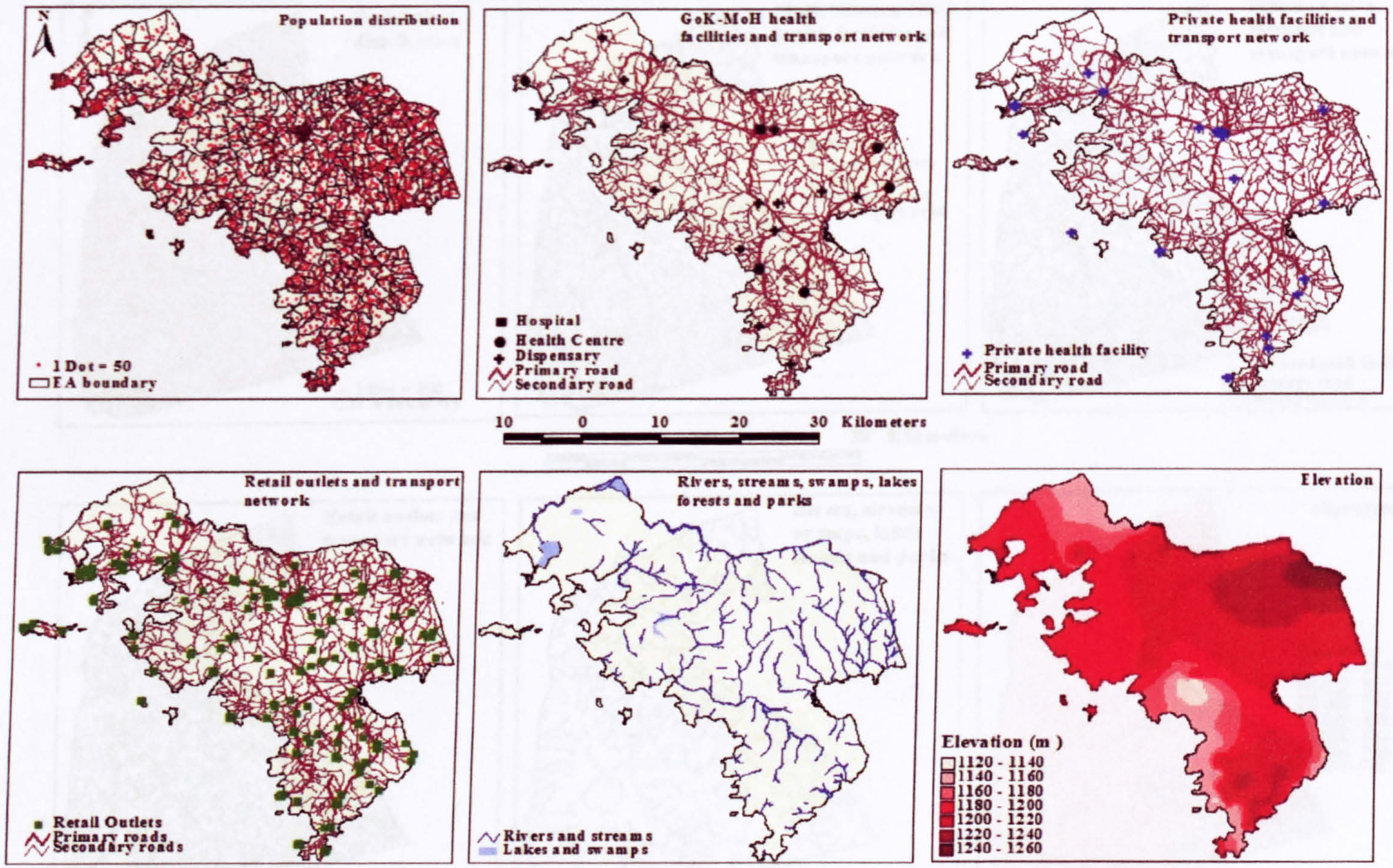
	Bondo		Greater Kisii		Kwale		Makueni	
	Health information	Ratio	Health information	Ratio	Health information	Ratio	Health information	Ratio
GoK-MoH	21	1:11,528	44	1:21,953	49	1:10,125	59	1:13,242
Mission/NGO	10	1:24,209	23	1:41,998	10	1:50,544	29	1:26,942
Private	22	1:11,004	118	1:8,186	38	1:13,301	113	1:6,914
Total	**53**	**1:4,567**	**185**	**1:5,221**	**98**	**1:5,157**	**201**	**1:3,887**
Doctors (% GoK-MoH)	8 (13)	1:30,262	61(34)	1:15,835	14 (29)	1:36,103	25 (24)	1:31,253
Clinical Officers (% GoK-MoH)	19 (32)	1:12,742	84 (42)	1:11,500	50 (68)	1:10,110	53 (36)	1:14,742
Nurses (% GoK-MoH)	66 (62)	1:3,668	553 (64)	1:1,747	269 (86)	1:1,880	325 (71)	1:2,404
Laboratory technologist/technician (% GoK-MoH)	24 (75)	1:10,087	123 (37)	1:7,853	56 (61)	1:9,025	41 (88)	1:19,057
Total (% GoK-MoH)	**117 (56)**	**1:2,070**	**821 (56)**	**1:1,177**	**389 (78)**	**1:1,300**	**444 (65)**	**1:1,760**
Beds (% GoK-MoH)	318 (28)	1:761	2,009 (26)	1:480	505 (82)	1:1,000	710 (57)	1:1,100
Microscopes (% GoK-MoH)	9 (4)	1:26,900	84 (18)	1:11,500	29 (31)	1:17,430	64 (25)	1:12,210
Retail Outlets	405	1:598	2,002	1:482	569	1:888	1034	1:756

Table 2.6 Transport network, water features, parks and forests, and elevation for the study districts

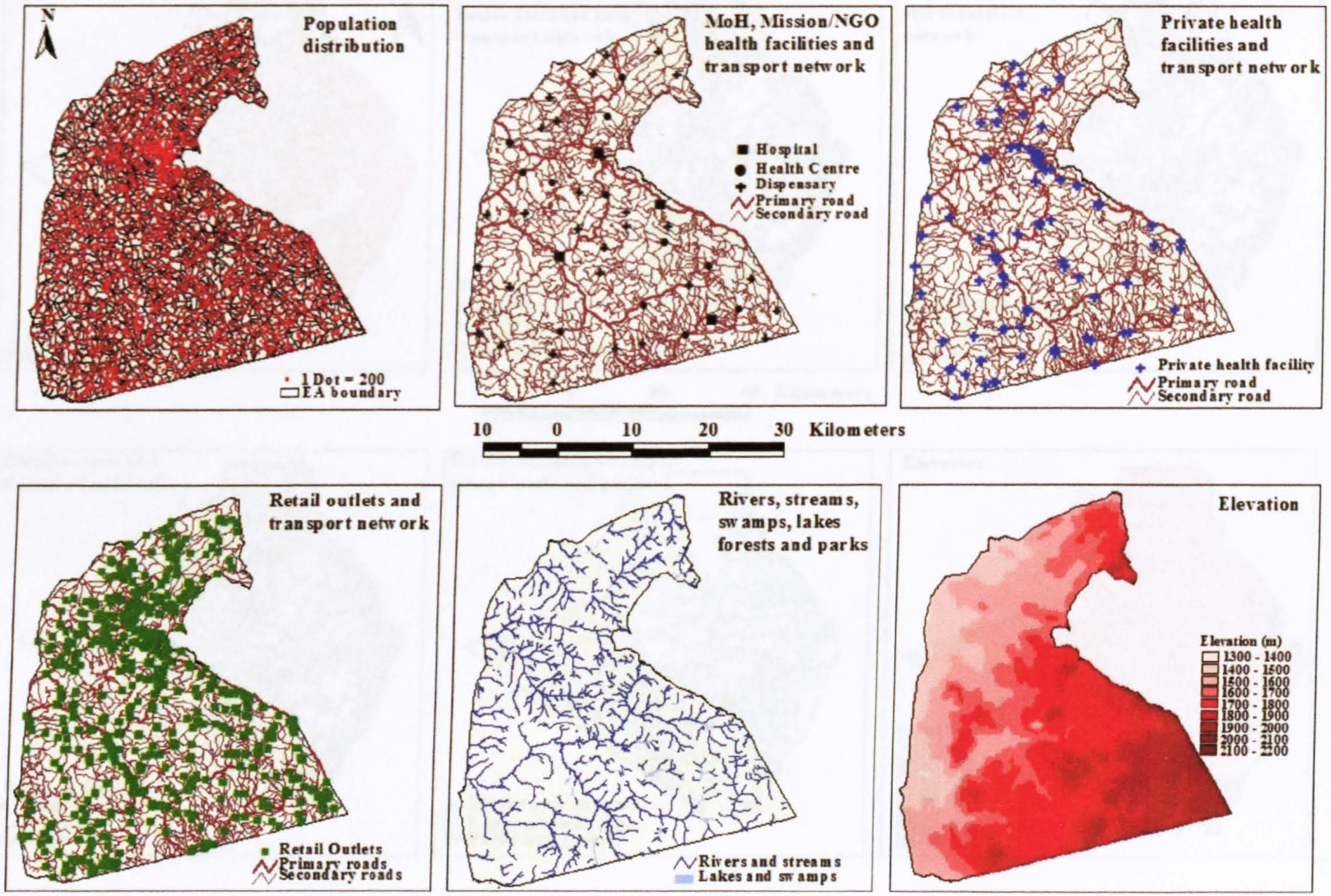
	Bondo	Greater Kisii	Kwale	Makueni
Transport network				
Primary roads	0.17 km^2	0.16 km^2	0.16 km^2	0.20 km^2
Secondary roads	1.80 km^2	1.80 km^2	0.60 km^2	0.80 km^2
Railway	0.00 km^2	0.00 km^2	0.01 km^2	0.02 km^2
Rivers & streams				
Seasonal rivers & streams	0.50 km^2	0.63 km^2	0.37 km^2	0.70 km^2
Perennial rivers	0.07 km^2	0.17 km^2	0.06 km^2	0.09 km^2
Lakes, dams and swamps	15 km^2	9 km^2	23 km^2	5 km^2
Gazetted parks and forest	0 km^2	0 km^2	294 km^2	1,274 km^2
Elevation				
Mean	1,198 m	1,703 m	127 m	1,042 m
Standard deviation	25 m	171 m	168 m	291 m
Maximum	1,258 m	2,153 m	917 m	1,980 m
Minimum	1,124 m	1,376 m	0 m	419 m

Figure 2.3 (a-d) Maps of the study districts showing GIS data of population, public and private health facilities, retail outlets, roads, rivers, swamps, lakes, parks ε elevation

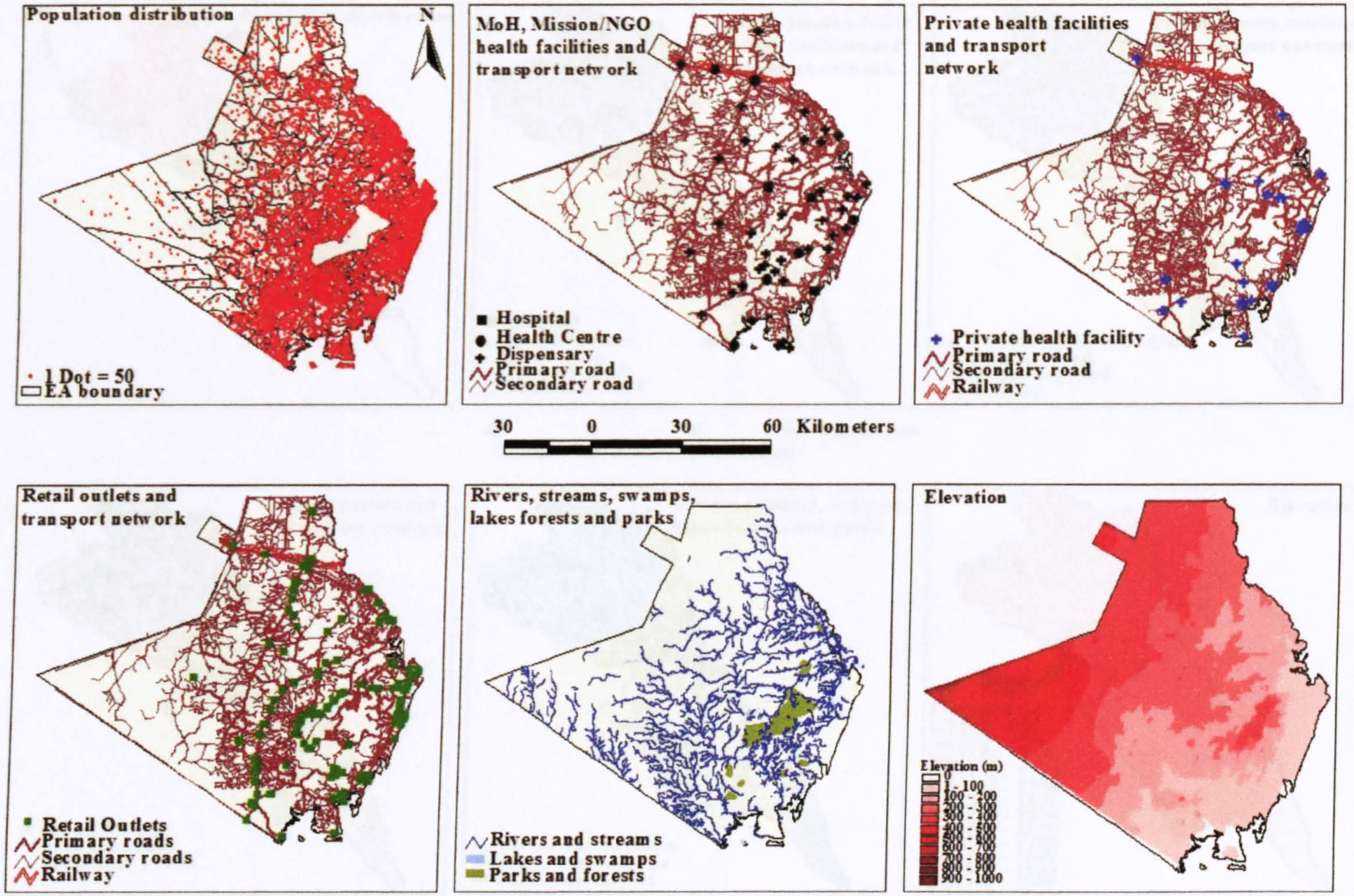
a) Bondo district



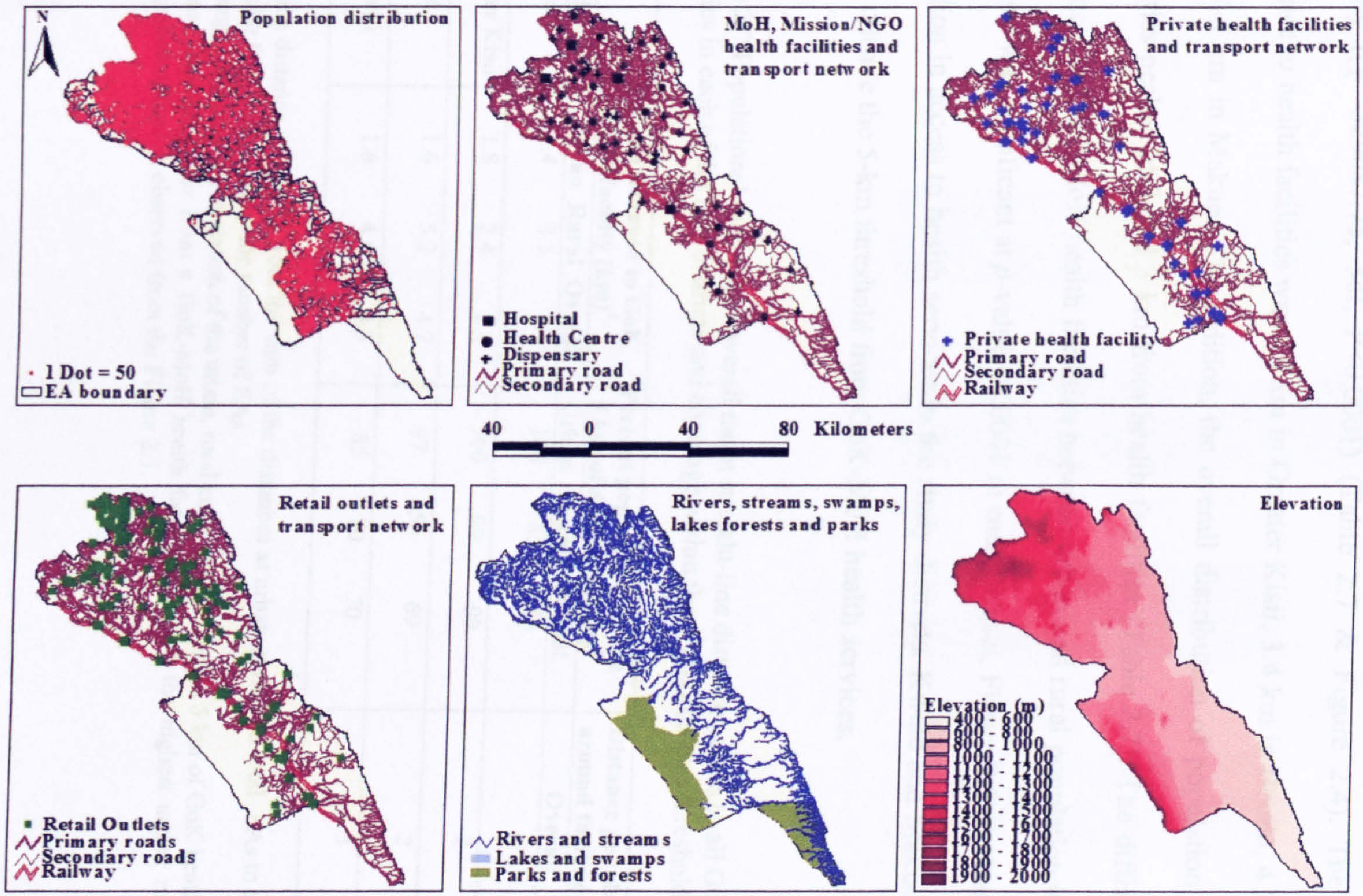
b) Greater Kisii district



c) Kwale district



d) Makueni district



2.6.2 Euclidean distance access to health service in the study districts

The analysis of Euclidean distances between communities and GoK-MoH health facilities revealed differences between districts, with 99% of the population in Greater Kisii, 86% in Bondo, 69% in Kwale and 70% in Makueni within 5 km of the nearest government health facility ((χ^2=329087.75, 3df, P<0.0001) (Table 2.7 & Figure 2.4). The overall mean distance to health facilities was 2.4 km in Greater Kisii, 3.4 km in Bondo, 4.7 km in Kwale and 4.5 km in Makueni. In addition, the overall distribution of population around health facilities peaked at 2 and 3 km from health facilities (Table 2.7). The difference in mean distances to GoK-MoH health facilities between urban and rural population within the four districts was significant at *p*-value <0.0001 in each district. Figure 2.5 represents the spatial variation in access to health services in the study districts. Kwale and Makueni show large areas outside the 5-km threshold from GoK-MoH health services.

Table 2.7 Populations' theoretical overall mean straight-line distance access to all GoK health facilities in each of the four districts and coverage within the five-kilometre threshold

	Mean distance to GoK health facility (km)[1]			**Percent population within 5 km of nearest facility[2]**			**Distance population around facilities peak (km)[3]**
District	**Urban**	**Rural**	**Overall**	**Urban**	**Rural**	**Overall**	**Overall**
Bondo	1.4	3.5	3.4	100	85	86	2
Greater Kisii	1.8	2.4	2.4	100	99	99	2
Kwale	1.6	5.2	4.7	97	56	69	2
Makueni	1.6	4.6	4.5	85	70	70	3

1. Mean distance computed from the sum of the distances at urban, rural and total EAs to the nearest GoK health facility divided by the number of EAs
2. Computed from the population of the urban, rural and total EAs within 5 km of GoK health facility
3. These were distances from a GoK-MoH health facility at which the highest urban, rural and overall population lived as observed from the Figure 2.5.

Figure 2.4 Percentage of population, in each district and all combined, within 5 km of GoK-MoH health facility based on Euclidean distances to the nearest facility

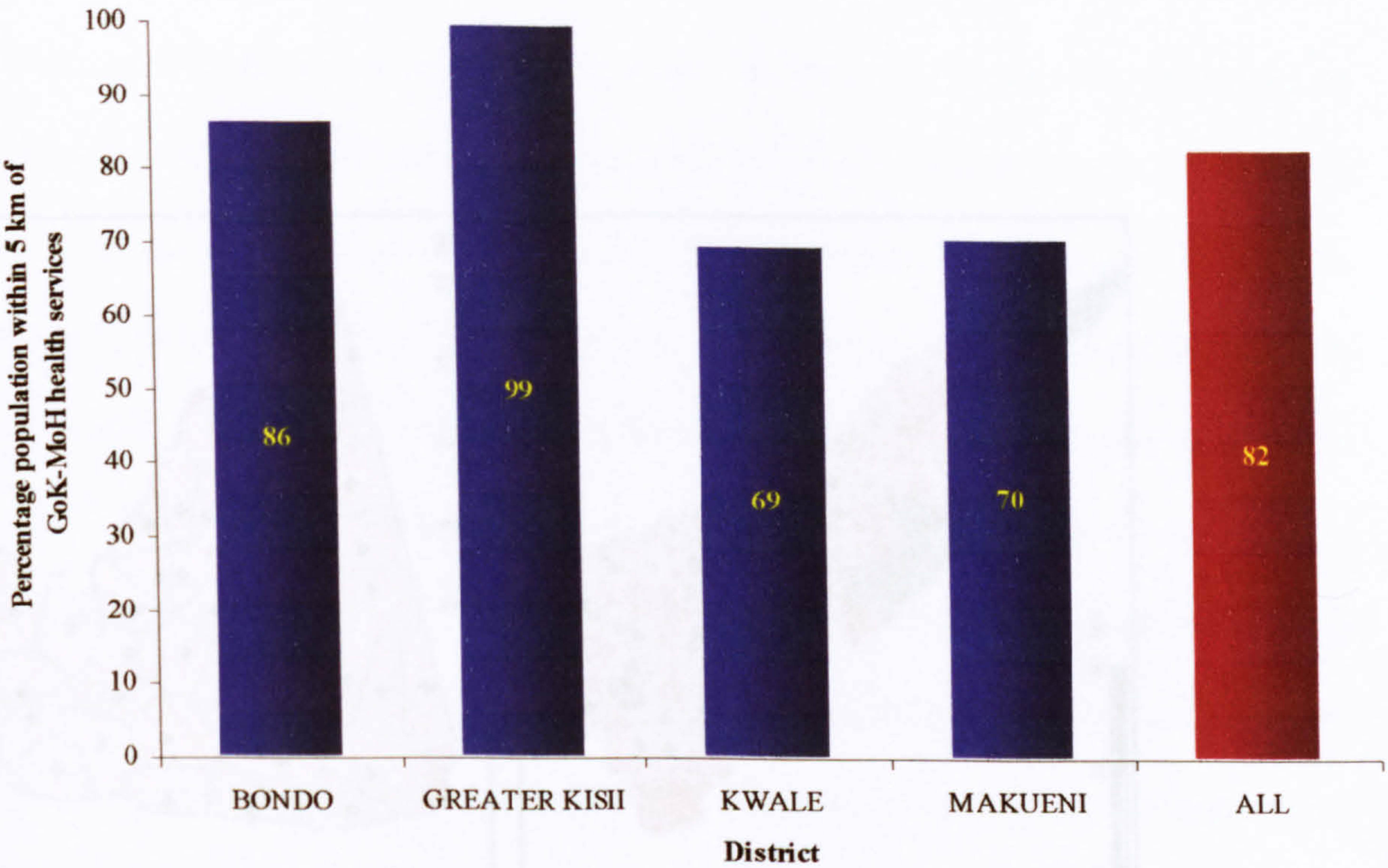
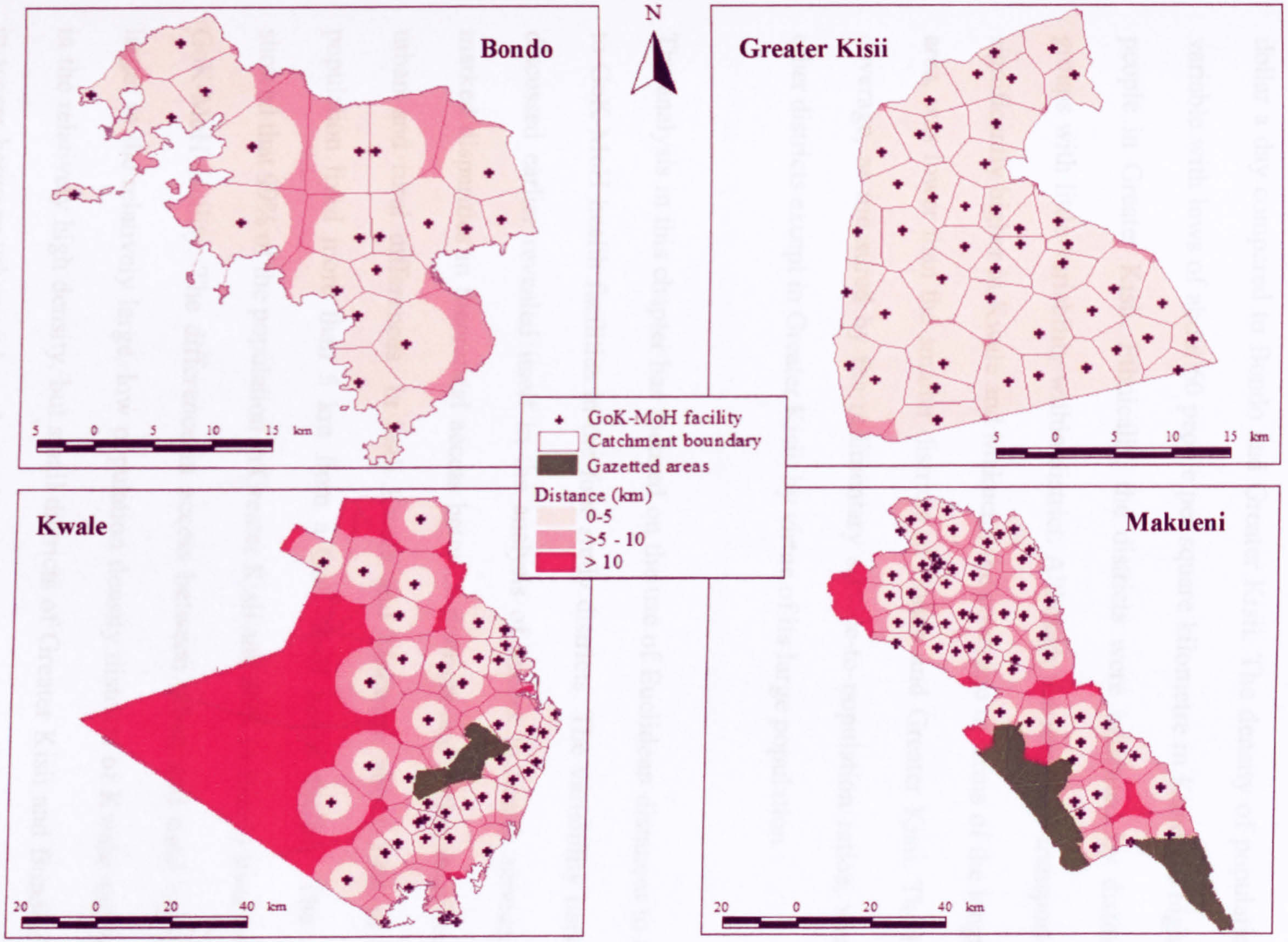


Figure 2.5 Maps of each of the four districts showing a continuous surface of populations overall access to Government health facilities



2.7 Discussion

The summary of the data revealed significant variability between the four study districts in terms of economy, demography, infrastructure, land cover and health services. Although the level of extreme poverty was consistent across all four districts, Kwale and Makueni were especially disadvantaged, having between 10-20% more people living on less than a dollar a day compared to Bondo and Greater Kisii. The density of population was highly variable with lows of about 60 people per square kilometre in Kwale to highs of over 700 people in Greater Kisii. Ethnically, the districts were inhabited by distinctly different groups with little variability within district. Although the length of transport network was significantly higher in Kwale and Makueni, the coverage in terms of the length of road per area, was lower than the smaller districts of Bondo and Greater Kisii. The health service coverage, as measured by the rudimentary service-to-population ratios, was close in all other districts except in Greater Kisii, by virtue of its large population.

The analysis in this chapter has focused on the use of Euclidean distances to define access to GoK-MoH health facilities in the four study districts. The variability between districts discussed earlier revealed itself in the analysis of access to health service. There were marked disparities in theoretical access between districts and within districts, particularly urban and rural differences. In both Kwale and Makueni, about 30% or more of the population lived more than 5 km from a GoK-MoH health facility. The analysis also showed that 99% of the population in Greater Kisii and 86% in Bondo lived within 5 km of GoK-MoH facility. The difference in access between urban and rural communities was larger in the relatively large, low population density districts of Kwale and Makueni than in the relatively high density, but small districts of Greater Kisii and Bondo. The inequity in access between urban and rural populations was lowest in Bondo and Greater Kisii (~ 1 km) and highest in Kwale and Makueni (~ 3 km). When all districts were combined, 82% of the population lived within 5 km of GoK-MoH health services.

In addition to self-reported travel time, the Euclidean model used here to measure distance between population and health services, represent what is commonly used to estimate national and international access to health care. If the results of this model for the four study districts were taken to represent the level of true spatial access to health care nationally, only 18% of the population are outside the 5 km target set out in the health reform strategy. This implies that Kenya will be on target to meet the health development goals specific to the coverage of effective preventive and treatment health services. It is critical, therefore, to ascertain the appropriateness of the Euclidean model's results in accurately estimating the level of access to health care in Kenya to ensure that country is indeed on target for its access-dependent health goals.

However, as discussed in Section 1.5.3, the limitations of the Euclidean model are its basic assumption that the actual routes people take to access health services can be sufficiently represented by the straight-line distances from their residences to services. Other inherent assumptions include: 1) that people will always use the nearest health facility; and 2) that, regardless of how access varies within a facility's catchment, use of that facility is constant. In the discussion of the limitations of measuring spatial access using the Euclidean approach, it was shown that in cases where the population and services are sparsely distributed it is likely to misrepresent the level of access to services (Section 1.6).

In the next chapter, an analysis aimed at testing how much actual use data from a GoK-MoH health facility survey of paediatric patients relates to the predicted use modelled in this chapter is performed. The two assumptions of the TP technique: that patients always use the nearest health facilities; and that utilisation rate is constant within a facility's service area is constant regardless of the level of access, are assessed. In Chapter 4, the differences in predicted access between the Euclidean models and other model based on the transport network are examined.

CHAPTER 3:
Utilisation of Government health facilities: the role of distance and the validity of the concept of use of nearest health services

3.1 Background

In the previous chapter, a Euclidean model was used to define spatial access to GoK-MoH health services and delineate catchment areas around them using the TP technique. A TP is defined in this case as the region that incorporates all points that are closer to a given facility than any other. The use of TP (also known as Dirichlet tiles) in estimating health facility catchments is well established (Section 1.5.3) and is based on two key assumptions. Firstly, it assumes that all patients choose to utilise the facility nearest to them, regardless of its type, hence the spatial extent of a facility catchment is determined solely by the proximity of neighbouring facilities in relation to the population. Secondly, it assumes that per-capita utilisation rate is constant throughout a catchment (i.e. distance does not deter utilisation within a catchment). In addition to the use of the TP technique, the analysis of distance in Chapter 2 based on the Euclidean principle assumes that people travel on straight-lines. Although the use of this approach is common and its attendant limitations well-documented, there is little empirical work aimed at quantifying these limitations and analysing their impact on estimates of spatial access to services.

In the first part of this chapter, the differences between theoretical straight-line distance criteria for potential health service access and use defined in Chapter 2, and the actual straight-line distances travelled by paediatric patients seeking malaria/fever case-management surveyed in the four study districts. The actual use data were obtained from a survey of 81 formal government health facilities in the four study districts involving interviews of 1,664 paediatric patients presenting with fever. The rationale behind the use of paediatric febrile patients as a tracer for the broader use of GoK-MoH health services is also given.

In the second part of the chapter the suitability of TP to define the health facility catchments is assessed. A series of new spatial analytical methods by which the validity of the associated assumptions are directly tested using the actual use data on paediatric fever patients are presented.

3.2 Rationale behind the use of paediatric febrile data as a tracer for service use

In Africa, fever is the most common presentation at health facilities among children (Snow *et al.,* 2003). Health workers in these countries often have to make treatment decisions without the aid of confirmatory laboratory tests (Redd *et al.,* 1992). Malaria has very similar clinical presentation to other infections making it hard to differentiate from conditions such as pneumonia, typhoid and bacteraemia (Akpede *et al.,* 1992; O'Dempsey *et al.,* 1993). In addition, even where microscopy is available and people are treated on the basis of slide results, many people in endemic areas have asymptomatic infections (Greenwood *et al.,* 1987). This makes it difficult to tell fevers in which parasites are the cause and those in which parasitaemia is coincidental. Consequently, fever is often treated presumptively as malaria (WHO, 1986). All multi-country studies in SSA on treatment seeking behaviour for malaria among children such as DHS (http://www.measuredhs.com) and Multiple Indicator Cluster Surveys (MICS) use fever as the entry point for investigating malaria treatment practices and is also used by the RBM initiative for measuring targets by 2010. Two issues are of importance when addressing the use of fever as a proxy for malaria: over- and under-diagnosis of the disease. Several studies have shown the poor specificity of presumptive treatment of malaria resulting in over-diagnosis of the disease with a large proportion of those treated for malaria being slide negative or having parasitaemia below cut-off (Mkawagile & Kihamia, 1986; Jonkman *et al.,* 1995; Olaleye *et al.,* 1998). However, it was also shown that this approach has high sensitivity for malaria resulting in most fevers which were true malaria treated as malaria (Greenwood *et al.,* 1987). Those febrile events among children not attributable to malaria were largely considered to be because of other infectious diseases with similar clinical presentations as malaria such as pneumonia, typhoid and bactreamia indicating fever as also a good proxy for several other acute infections. TB and HIV/AIDS are presently predominantly adult diseases in Africa and are therefore not well-represented in the paediatric febrile data used in this thesis. The data does not also represent use of services by adults, in-patients and for chronic ailments such as cancer. For these practical reasons, therefore, any resource allocations aimed at combating malaria and other acute infectious diseases among children in SSA will inevitably have to fever as an entry point. In the clinics used in this study fever is treated presumptively as malaria and at the homesteads fever is used as an proxy of for malaria treatment seeking patterns similar to DHS and MICS studies.

In Africa, the malaria burden is largely borne by young children with 68% of the malaria mortality and 48% of the morbidity burden among children aged <5 years (Snow *et al.*, 2003). In Kenya, malaria accounts for more than 8 million outpatient treatments at GoK-MoH health facilities each year, representing over a third of all out-patient diagnoses (MoH, 2001). Moreover, GoK-MoH and other formal health services provide treatment for over 46% of all fevers in young children (CBS, 2003). Kenya, in common with most SSA countries, inappropriate distribution of limited health resources, improper access to and utilisation of existing health services and the increasing occurrence of drug resistant malaria pose challenges for the national government (MoH, 2001). As such, government services can become overwhelmed.

The *national malaria strategy* (NMS) was launched in April 2001 with the overriding aim of ensuring coordinated, multi-lateral, national response that harnesses Roll Back Malaria (RBM) and reflects the countries policies on health sector reform and poverty eradication. To this end four strategic approaches were outlined for which the government health sector is a key delivery channel;

1) Ensuring access to quick and effective treatment to significantly reduce illness and death from malaria

The first and second line antimalarials (Sulpahdoxine Pyremethamine (SP) and Amodiaquine (AQ) respectively) were shown to have diminished and rapidly declining efficacy against the malaria parasite (EANMAT, 2003). In April 2004, following a series of Technical Working Group meetings, technical support from Roll Back Malaria, Geneva and support from AFRO/WHO, the Ministry for Health announced that Kenya would abandon SP as its first-line therapeutic for malaria and this would be replaced by Coartem® (DOMC, 2004). An application was submitted to the Global Fund for AIDS, TB and Malaria (GFATM) to consider the full funding of the drug requirements for the government formal health sector over five years. In June 2004 the GFATM announced that Kenya was successful in its application and a total of 81 million US dollars were released. The policy will be staggered beginning with ensuring access to Coartem® in the government health sector and by the fourth year establishing mechanisms for Coartem® access in the informal retail sector. As such information on the distribution and location of government health services in relation to the distribution of population and the nature of spatial access to these services is critical for the immediate roll-out of the ACT programme.

2) Provide malaria prevention measures and treatment to pregnant women,

Malaria contributes to high morbidity and mortality among pregnant women in Kenya and other SSA countries. In one study malaria related anaemia was estimated to contribute 3.7% of maternal mortality in SSA (Snow *et al.*, 2003). An estimated one million malaria associated low birth weight children are born in Africa each year, 40% of whom die before the age of five years (Guyatt and Snow, 1999). Intermittent presumptive treatment (IPT) of pregnant mothers is the recommended approach for reducing the burden of malaria among this population group. In Kenya, this is done through the provision of antenatal care (ANC) almost exclusively at government health services.

3) Ensure use of insecticide-treated nets (ITNs) by at risk communities to significantly reduce rates of disease

The efficacy of ITNs in reducing the burden of malaria is well documented (Lengeler, 2001; Philips-Howard *et al.*, 2003). However, there is an ongoing debate on how best to make them accessible to communities. In Kenya, the Ministry of Health (MoH) has plans to distribute ITNs to all government health facilities as project integrated within the broader immunisation campaign schedule for the year 2005.

4) Improve epidemic preparedness and response. For each strategic approach several targets were outlined to be achieved by the year 2006. The MoH disease surveillance unit uses selected government health services for purposes of collecting information relevant to detecting epidemic in advance and thereby contributing to the government's preparedness.

Nonetheless, it is acknowledged that the private and other non-governmental health sectors play an important role in the delivery of health services in Kenya. To this end a considerable effort has gone into developing a national database of shops and private health facilities (Section 2.4.2 & 2.4.3). However, the spatial accessibility modelling exercise in this thesis is for government health facilities only. Firstly, most of the malaria interventions for which fever is a proxy and which require monitoring and evaluation usually begin with the government health sector. More importantly, sufficient data is not available for the non-governmental sector to enable the inclusion of this sector in the modelling exercise in this thesis.

3.3 Methods

3.3.1 District level GIS data

The study was undertaken in the four districts described in Chapter 2. The development of the district-level GIS data of service providers and population is presented in detail in the Section 2.4.1 & 2.4.2. Population data were expressed within the GIS platform at the Enumeration Area (EA) level (Section 2.4.1).

3.3.2 Health facility surveys

A series of quality-of-care cross-sectional surveys were conducted at government health facilities in Bondo, Greater Kisii, Kwale and Makueni districts in Kenya between July 2001 and February 2002. A total of 81 GoK-MoH health facilities were sampled. Health workers' malaria case-management practices were observed as they performed outpatient consultations for sick children under five years of age. Stratified, cluster sampling was used to select consultations. A cluster was defined as all sick-child consultations occurring at a facility over two consecutive days and strata were defined by health facility size and caseload. Facilities with an average of less than five sick-child consultations per day were excluded from the sampling frame. Among the remaining facilities, three strata were defined: 1) small health facilities (dispensaries), 2) health centres and small hospitals, and 3) district hospitals (each district had only one district hospital). Within strata 1 and 2, facilities were randomly selected; for stratum 3, the district hospital in each district was included (Zurovac *et al.*, 2002; 2004).

Two survey teams were used in each district during the peak malaria seasons comprising a clinical officer acting as an observer of the clinical consultation of health workers by sick children and nurses who interviewed mothers or normal guardians on exiting the facility. Each team was assigned one facility per day over two days at which caretakers of febrile paediatric patients attending the health facilities were asked to provide information on the patient's home village or EA, village and household heads, nearest school, bus stop and health facility using a structured questionnaire (Appendix 2). Using this information, the correct EA was assigned to each patient. Where correct information on the patient's EA was not provided, information on the household head, village head, nearest school and bus stop was used to attribute the patient's home to the village or EA, through repeat field visits until all patients were located.

3.3.3 Analytical Methods

3.3.3.1 Analysis of actual usage of health facilities

For each patient the straight-line distance from the EA of residence to the health facility where treatment was sought was computed. Using an 11-point scale, the number of patients that used a health facility at each distance point was derived for each district. In addition, the mean distances travelled by users in a district were derived. The facilities were grouped into hospitals, health centres and dispensaries and the sum of patients that used facilities of different types computed. The mean distances travelled by facility type were then calculated to establish variation in use by facility type. Users were also classified into urban and rural and mean distances travelled by each class analysed. To establish the overall effect of distance on the use of health facilities, the relationship between the numbers of patients that used a facility on an 11-point distance scale, both as a discrete and as a cumulative use, was plotted. To determine the nature of health facility's usage against the 5 km threshold, the percentage of patients that used a health facility within this distance in each district was derived. Users were colour coded based on whether they used a facility within five kilometres or outside and these were superimposed on the potential usage surface maps to compare the relationship between actual use against the underlying distance predicted use.

Statistical comparisons in each district between the cumulative percentage of potential users of the facilities used in the study and the corresponding actual users at the 11-point distance scale were made. A logarithmic transformation of the percentages (since the relationship between distance and both potential and actual facility use was positively skewed) was performed (Kirkwood & Sterne, 2003). Simple linear regression was used to test the correlation between potential use based on distances to nearest facility and actual use revealed in the survey.

3.3.3.2 Assessing the validity of the assumptions in the Thiessen polygon techniques

3.3.3.2.1: Defining health facility catchment boundary between two adjacent facilities

The 81 facilities in the data were drawn from a sample of the 173 GoK-MoH facilities found in the four districts. Thiessen polygons were created around all 173 facilities. It was then possible to identify cases where two sampled facilities were immediately adjacent, that is, they shared a catchment boundary. A total of 78 such pairs were identified in the four districts. Analysis was performed along a transect line that joined the two facilities in each pair.

Each of the 78 pairs of neighbouring facilities was considered in turn. In each case, a *fuzzy choice* value was assigned to every EA that contributed one or more patients to either facility in the pair. This value was simply the relative proportion of patients attending each facility from a given EA. The two facilities in each pair were labelled A and B such that values ranged from one (all to A) to zero (all to B). To ease later analysis, facilities were assigned as A or B in a consistent manner depending on the type of facilities in question. This meant that each pair was always classed as health centre-to-dispensary, dispensary-to-hospital, or health centre-to-hospital and not in the opposite order. The opposite relationships need not be considered separately as they are simply the inverse of those considered. Pairs of matching facility type were also considered, and in these cases facilities were assigned as A or B arbitrarily. Fuzzy choice values were assigned to the EA polygon coverage. These vector layers were converted into 100 m by 100 m raster grids and interpolated using an IDW algorithm. The result was a *patient's fuzzy choice surface* which represented a continuous prediction of patient choice behaviour between the two neighbouring facilities. Each fuzzy choice surface was analysed along the transect line between the two facilities in question. Each transect was divided into 100 equally spaced points and the fuzzy choice value recorded at each point. This process was implemented using the ArcView *X-Section Utility v1.0* extension. The catchment 'choice boundary' was taken to be located at the point where the fuzzy choice value equalled 0.5 (Gething *et al.*, 2004). For each of the transect classes an 'average' transect was created by calculating the mean fuzzy choice value for each of the 100 divisions. In this instance, relative distances were considered since the split of patients between neighbouring facilities is of interest, regardless of the absolute distance between them.

The relative location of the 0.5 (50%) fuzzy choice boundary was also recorded for each transect. A TP boundary would be located at the exact mid-point of a given transect (50%, since transects ran from zero to 100%). Actual boundary locations less than 50% are closer to facility A, while those greater than 50% are closer to facility B. An overall and district mean transect location was calculated for each transect class. To compare the means of the transect locations of adjacent health facilities, single sample *t*-tests were carried out on the overall mean of each class. For the dispensary-to-dispensary and health centre-to-health centre classes a two-tailed test was applied to test for a significant difference from the Thiessen boundary (i.e. from a mean value of 50%) because the similarities of type of the two adjacent health facilities in each transect case. For the remaining three transect classes a one-tailed test was used. Hospitals are the highest-order facility followed by health centres and then dispensaries. The expectation is that any deviation from the TP boundary will probably be due to patients choosing to make a longer journey to reach a higher-order facility, resulting in a displacement from the TP boundary in favour of the higher -order facility.

3.3.3.2.2: Assessing variation in utilisation rate within catchments

In this section, the one other inherent assumption of the TP technique, that utilisation of a health facility is uniform within its catchment regardless of the distance of users from facility, was investigated. To isolate the effect of distance on utilisation rate for each facility it was necessary to define each catchment such that the influence of a neighbouring facility could be considered minor. This was achieved by shrinking the TP boundaries of each catchment, such that radii were reduced by approximately 25%. This figure exceeded the largest mean deviation from a TP position found in the analysis of patient choice. This strategy was implemented by creating an exclusion buffer. The buffer width was calculated as a function of the area of each polygon. If polygons can be assumed to be approximately square then the width W of buffer required to achieve a reduction in radius of 25% can be defined in terms of the polygon area A as:

$$W = 0.25\frac{\sqrt{A}}{2} \qquad \text{(Equation 3.1)}$$

Buffers were created at this width for each catchment. For each sampled facility, utilisation rate was calculated for each EA contributing one or more patients (excluding those contributing zero patients). This value was obtained simply by dividing the tally of recorded patients from a given EA by its population. When dealing with paediatric data, the use of total population as a denominator is clearly less favourable than child-only totals. Furthermore these values represent a daily rate that may not be amenable to extrapolation across the year. To achieve a more readily comparable value, the absolute EA rate values for each facility were transformed into relative utilisation rate (RUR) by dividing each set through by its largest value. These RUR values were linked back to the EA polygon coverage and again rasterised into a 100 m by 100 m grid. The catchment area for each facility was then delineated using the exclusion buffers. For each of the 81 study catchments the RUR value of every grid cell was output along with its six-digit latitude and longitude. The straight line distance between a given facility and the centroid of each non-zero cell in its study catchment was calculated. RUR values were then grouped by distance from facility and a mean value was calculated for every successive 100 m. An overall mean RUR plot was created along with one for each district. These plots illustrate the influence of distance from facility on RUR. In contrast to the analysis of patient choice, utilisation rate is considered with reference to absolute distance.

3.4 Results

3.4.2 Health facility surveys

The study of GoK-MoH health service use for the treatment of paediatric fevers sampled a total of 81 health facilities: 19 health facilities in Greater Kisii; 17 in Bondo; 21 in Makueni; and 24 in Kwale, in which 463, 395, 388 and 422 paediatric patients were assessed, respectively. The distribution of the sampled health facilities is represented in Figure 3.1. The usage patterns of services by febrile paediatric patients in the districts showed that 80% in Greater Kisii, 84% in Bondo, 64% in Kwale and 65% in Makueni used a government health facility at five kilometres with the five- to six-kilometre distance being the location of the point of inflection where the rate of change of usage slowed (Figure 3.2). There was a general reduction in number of patients using health facilities as distance from facilities increased, with major peaks at 2 or 3 kilometres in the four districts (Figure 3.3).

There was a marked disparity between and within the districts in terms of the overall mean distances travelled by the febrile patients to the GoK health facility where treatment was sought. To account for the variation in standard deviation when comparing means, a sample t-test was used and showed that the differences between the mean distances travelled by rural compared to urban paediatric patients to access treatment were significantly higher in the larger districts of Kwale and Makueni ($p < 0.0001$), but also significant in Bondo ($p= 0.04$) and Greater Kisii ($p=0.003$).

Users in both Kwale and Makueni districts, whose populations had relatively poor access to government health services, travelled a mean distance of 5.4 km while those in Greater Kisii and Bondo travelled mean distances of 3.9 km and 3.2 km respectively.

Figure 3.1 Maps of distribution of GoK-MoH health facilities in the study districts

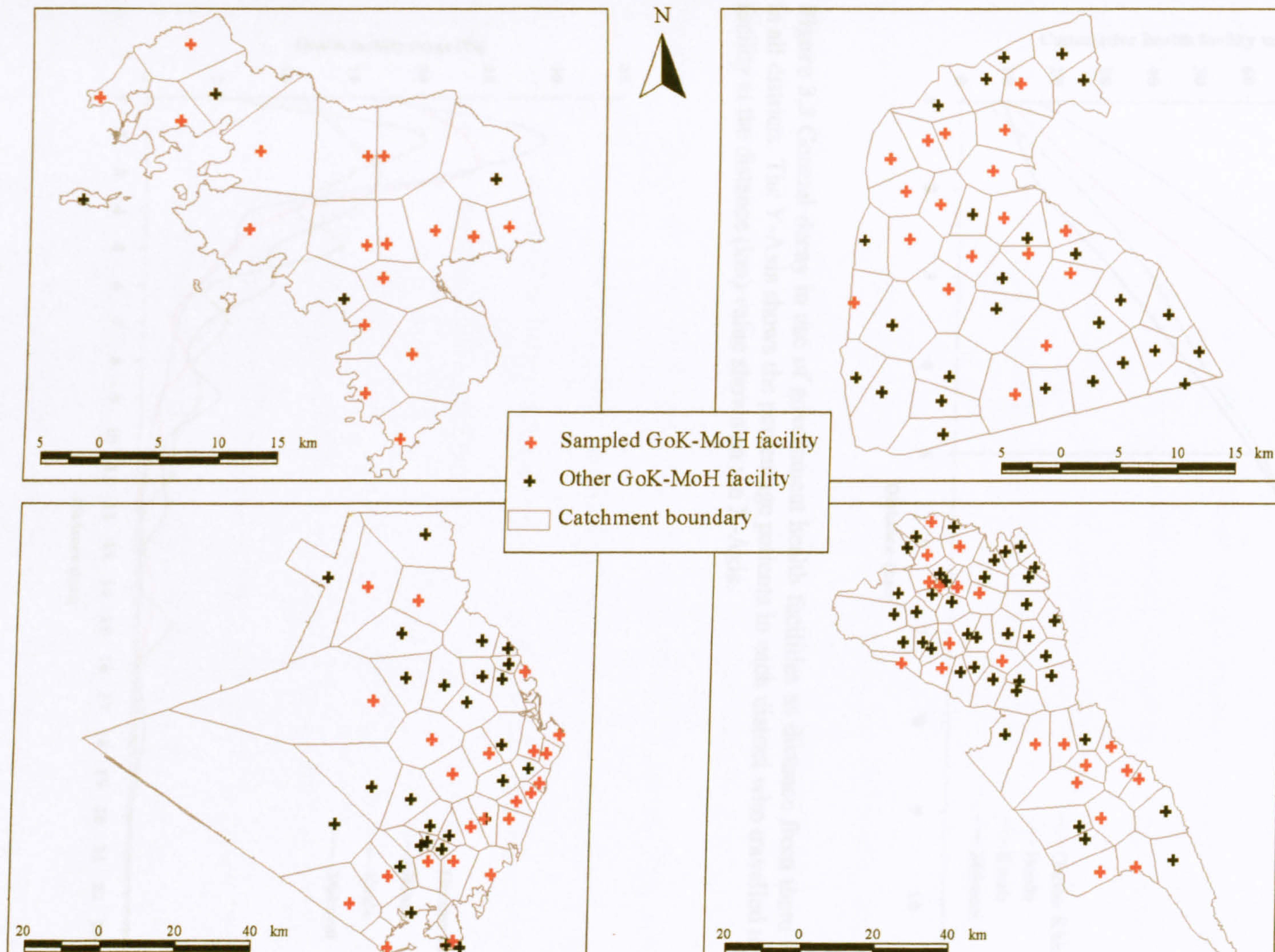


Figure 3.2 Cumulative health service use against distance travelled to Government health facility where treatment was sought for the four districts. The Y-Axis shows the cumulative percentage of patients in each district who travelled to a health facility at the distance (km) value shown on the X-Axis.

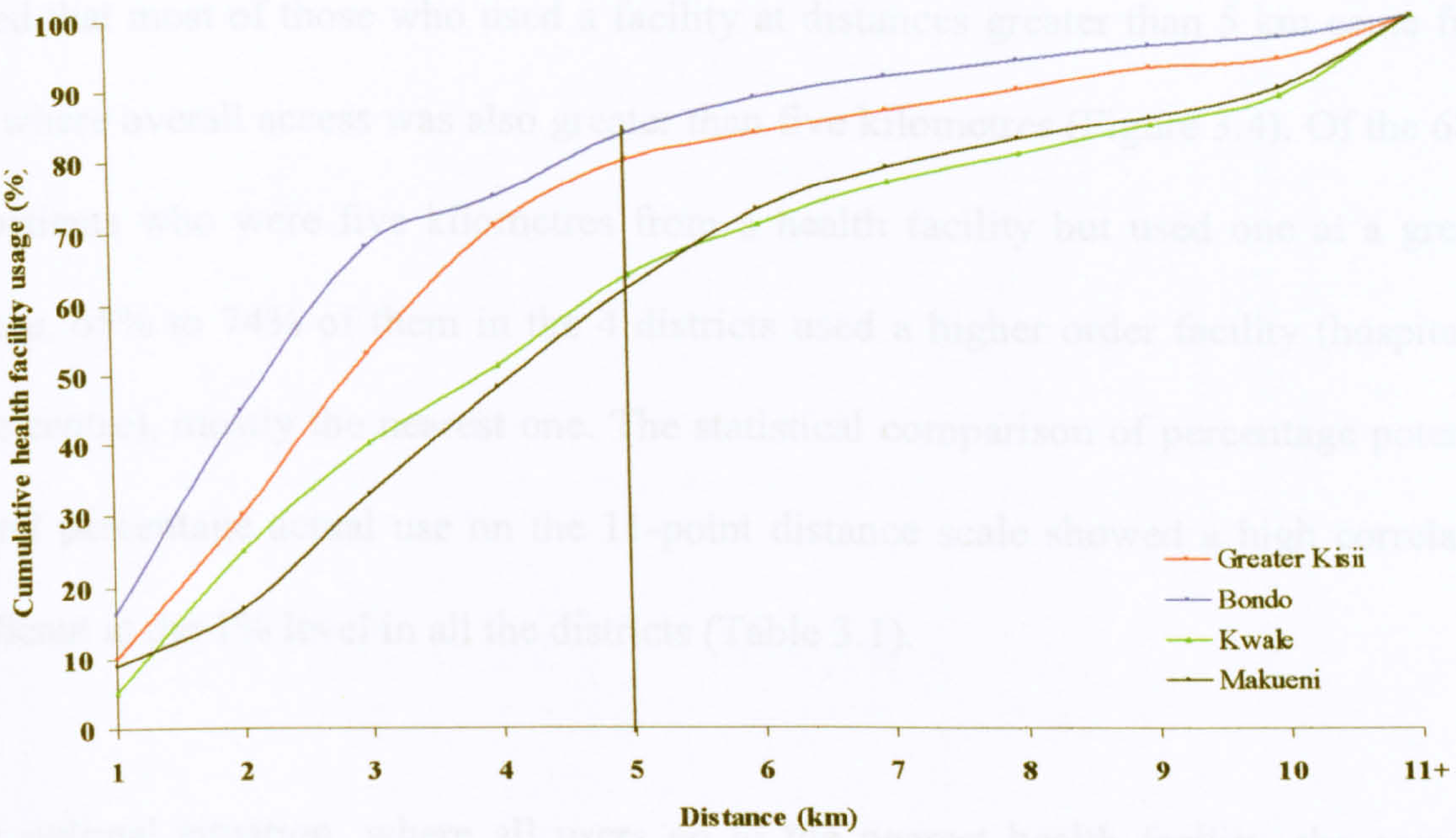
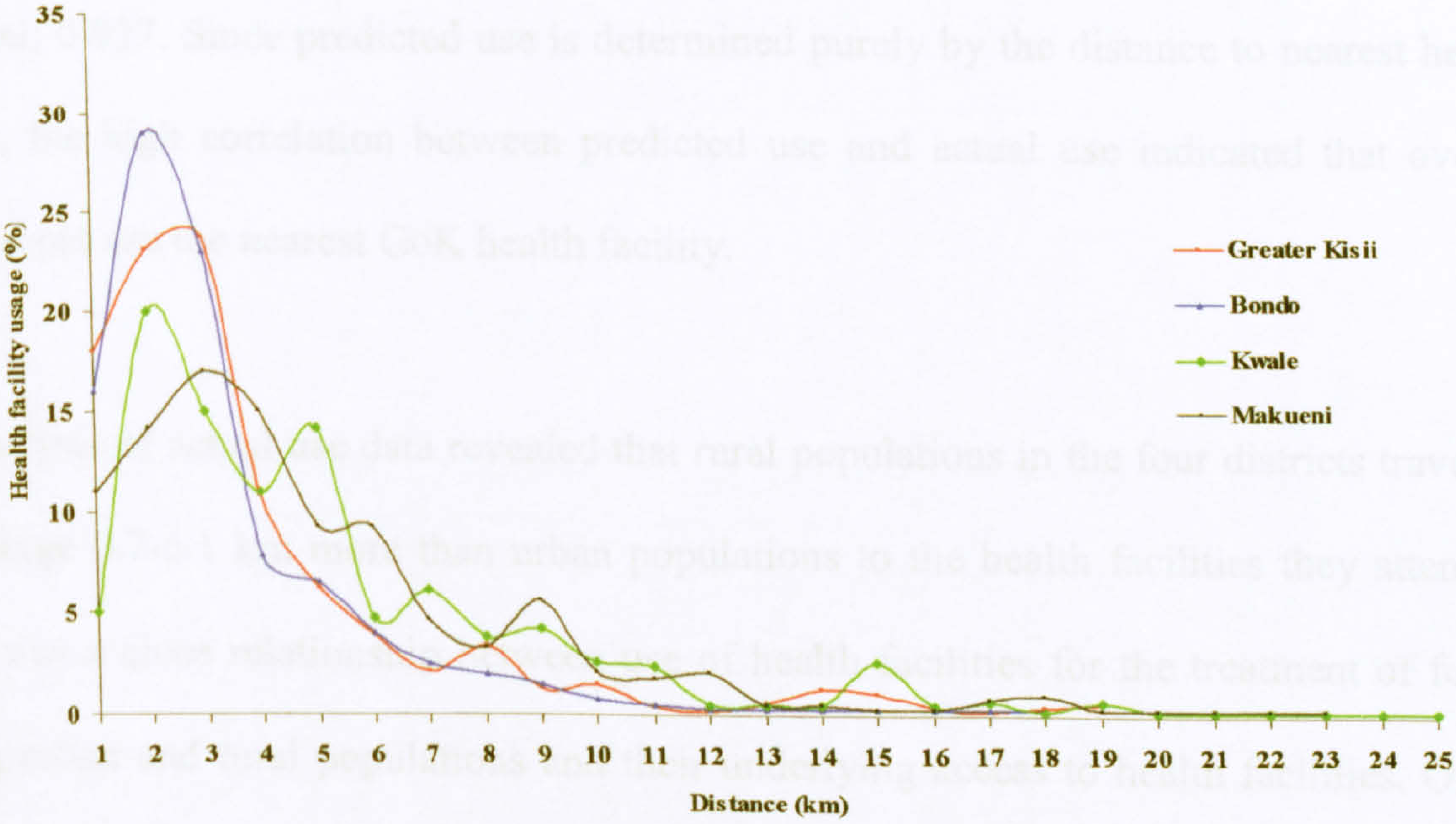


Figure 3.3 General decay in use of government health facilities as distance from them increased in all districts. The Y-Axis shows the percentage patients in each district who travelled to a health facility at the distance (km) value shown on the X-Axis.



Overall, patients travelled greater distances to hospitals than to health centres and dispensaries (Table 3.1). Most patients, 56% in Greater Kisii, 68% in both Kwale and

Makueni and 83% in Bondo, used the nearest government health facility.

The overlay of actual users classified into those using a facility within or outside 5 km showed that most of those who used a facility at distances greater than 5 km came from areas where overall access was also greater than five kilometres (Figure 3.4). Of the 68 to 205 patients who were five kilometres from a health facility but used one at a greater distance, 65% to 74% of them in the 4 districts used a higher order facility (hospital or health centre), mostly the nearest one. The statistical comparison of percentage potential use and percentage actual use on the 11-point distance scale showed a high correlation significant at the 1% level in all the districts (Table 3.1).

In an optimal situation, where all users go to the nearest health facility, the correlation between the percentages of distance predicted potential users and that of actual users revealed in the survey would have a value of one. The statistical analysis revealed a Coefficient of Determination (R^2) in Greater Kisii of 0.879; Bondo 0.706; Kwale 0.996; Makueni; 0.927. Since predicted use is determined purely by the distance to nearest health facility, the high correlation between predicted use and actual use indicated that overall most people use the nearest GoK health facility.

The analysis of actual use data revealed that rural populations in the four districts travelled an average 0.7-5.1 km more than urban populations to the health facilities they attended. There was a close relationship between use of health facilities for the treatment of fevers among urban and rural populations and their underlying access to health facilities. Of the patient population seen at the facilities, over 90% of the attendees were from rural areas (Table 3.1). Rural areas in these districts are home to over 85% of the population (Section 2.6).

Table 3.1 Number of paediatric patients who attended GoK health facilities during the study period and their patterns of use of health facilities for the treatment of fevers determined by distances travelled

District	Number of patients interviewed			Mean distance Travelled to health facility (km)			Percent patients using nearest facility	Correlation between distance predicted and actual use of health facilities*
	Urban	Rural	Total	Urban	Rural	Overall		
Greater Kisii								
Hospitals	25	144	169	2.6	5.9	5.5	43 (72)	R^2=0.879
Health Centres	0	89	89	-	3.3	3.3	54 (48)	P =<0.01
Dispensaries	3	202	205	5.4	2.7	2.8	67 (138)	
Total	**28**	**435**	**463**	**2.9**	**3.9**	**3.9**	**56 (258)**	
Bondo								
Hospitals	22	48	70	1.2	5.8	4.4	74 (52)	R^2=0.706
Health Centres	6	101	107	5.0	3.1	3.2	76 (81)	P =<0.01
Dispensaries	6	212	218	4.3	2.7	2.7	89 (194)	
Total	**34**	**361**	**395**	**2.5**	**3.2**	**3.2**	**83 (327)**	
Kwale								
Hospitals	28	65	93	3.4	8.1	6.8	61 (57)	R^2=0.996
Health Centres	12	97	109	4.1	6.0	5.8	53 (58)	P =<0.01
Dispensaries	15	205	220	1.2	4.9	4.7	79 (173)	
Total	**55**	**367**	**422**	**2.9**	**5.8**	**5.4**	**68 (288)**	
Makueni								
Hospitals	9	62	71	0.4	6.5	5.9	72 (44)	R^2=0.927
Health Centres	4	162	166	0.5	5.1	5.5	60 (100)	P =<0.01
Dispensaries	0	151	151	-	4.9	4.9	78 (118)	
Total	**13**	**375**	**388**	**0.5**	**5.6**	**5.4**	**68 (262)**	

* A logarithmic transformation was performed of percentage potential and actual use at similar distances and used a simple linear regression to test the correlation between potential use based on distances to nearest facility and actual use revealed in the survey.

The predicted GoK health service use for the four districts used in the analysis so far was derived from health facility catchments based on the TP technique. This technique assumes that all patients choose to utilise the facility nearest to them, regardless of its type, and hence the spatial extent of a facility catchment is determined solely by the proximity of neighbouring facilities in relation to the population. It also assumes that per-capita utilisation rate is constant throughout a catchment (i.e. that distance does not deter utilisation within a catchment). In the following two sections the results on the validity of these assumptions are presented.

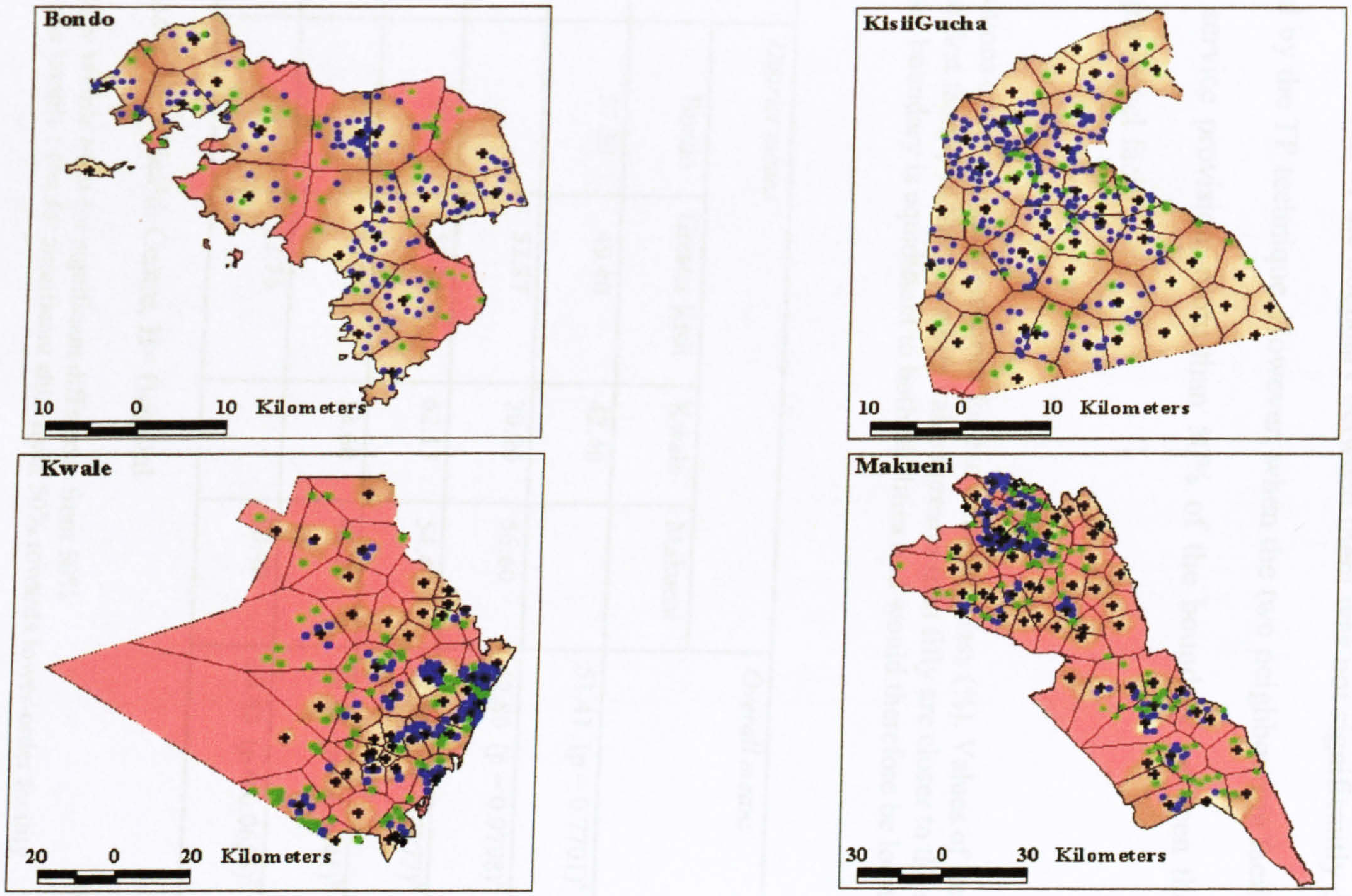
3.4.3 Assessing the validity of the assumptions in the Thiessen polygon techniques

3.4.3.1 Defining health facility catchment boundary between two adjacent health facilities

Out of the 81 GoK-MoH health facilities involved in the study, a total of 78 pairs of neighbouring facilities were identified in the four districts and an analysis was performed along the transect line that joined the two facilities in each pair (Figure 3.5).

The mean fuzzy choice transect values are shown for the three classes of differing facility type that were present; health centre-to-dispensary, dispensary-to-hospital, and health centre-to-hospital, for each district, and overall (Figures 3.6a-d & 3.7). In each case the position of the 0.5 fuzzy value point (the point on the boundary at which a patient is equally likely to use either of the health facilities) is shown. This point was taken to represent the actual use catchment boundary and in each case it was located nearer the lower order facility. In both Bondo and Makueni district, there was insufficient data to plot the relationship between health centres and hospitals. Since not all districts had sufficient data to plot all the facility relationships the data were aggregated. Table 3.2 lists the overall and district mean boundary locations for all five transect classes. The overall mean boundary locations were 51.4% for dispensary-to-dispensary, 49.8% for health centre-to-health centre, 58.5% for health centre-to-dispensary, 39.9% for dispensary-to-hospital and 38.6% for health centre-to-hospital.

Figure 3.4 District maps showing EAs, where patients came from, as represented by centroid of EA polygons, the health facilities they used and the underlying overall access to health services. The EAs have been classified into those where patients travelled ≤ 5km (blue *centroid* point) and those > 5km (green *centroid* point). There was a close relationship between distance travelled by patients and the population's underlying access to GoK health facilities with varying shades of brown representing areas with access distances between less than <1 km to 5 km and the red colour representing areas greater than 5 km [<1km, >1-2 km, >2-3km, >3-4 km, >4-5 km and >5 km]. The figure also shows the facilities catchment areas and the position of the facilities [ ] used in the study for each district.



Two-tailed single sample *t*-tests for the dispensary-to-dispensary and health centre-to-health centre classes both revealed no significant difference from the TP location of 50% (p=0.7701 and p=0.9798 respectively). One-tailed single sample *t*-tests for the remaining three classes revealed that boundary locations were significantly nearer the lower-order facility in each case (Table 3.2). This meant that where the two neighbouring facilities were of the same type, the location of the boundary between them was not significantly different from that predicted by the TP technique. However, when the two neighbouring facilities are of different level service provision, more than 50% of the boundary between them was assigned to the higher-level facility.

Table 3.2 Mean positions of catchment boundaries for each transect class (%). Values of less than 50% are closer to the first facility in the pair while values greater than fifty are closer to the second. A theoretical Thiessen boundary is equidistant to both facilities and would therefore be located at exactly 50%.

Transect class	*District means*				*Overall means*
	Bondo	Greater Kisii	Kwale	Makueni	
D-D	57.30	49.40	42.40		51.41 (p = 0.7701)[a]
HC-HC		52.87	20.20	56.60	49.80 (p = 0.9798)[a]
HC-D	61.31	55.25	62.17	54.40	58.50 (p = 0.0077)[b]
D-H	37.30	39.05	38.60	46.70	39.88 (p = 0.0041)[b]
HC-H		32.75		50.40	38.63 (p = 0.0656)[b]

D= Dispensary, HC= Health Centre, H= Hospital

[a] two-tailed single sample *t*-test for significant difference from 50%
[b] one-tailed single sample *t*-test for significant shift from 50% towards lower-order facility

Figure 3.5 Creation of a *fuzzy choice* surface. This example shows the case of Iyabe health centre and Misesi dispensary in the Greater Kisii district. All EAs contributing one or more patients to either facility are allocated a fuzzy choice value corresponding to the relative proportion attending Iyabe health centre (a). The polygon coverage was then rasterised into a 100m grid and interpolated using an inverse distance weighting algorithm to estimate a choice surface (b). Thiessen polygon boundaries are also shown for reference.

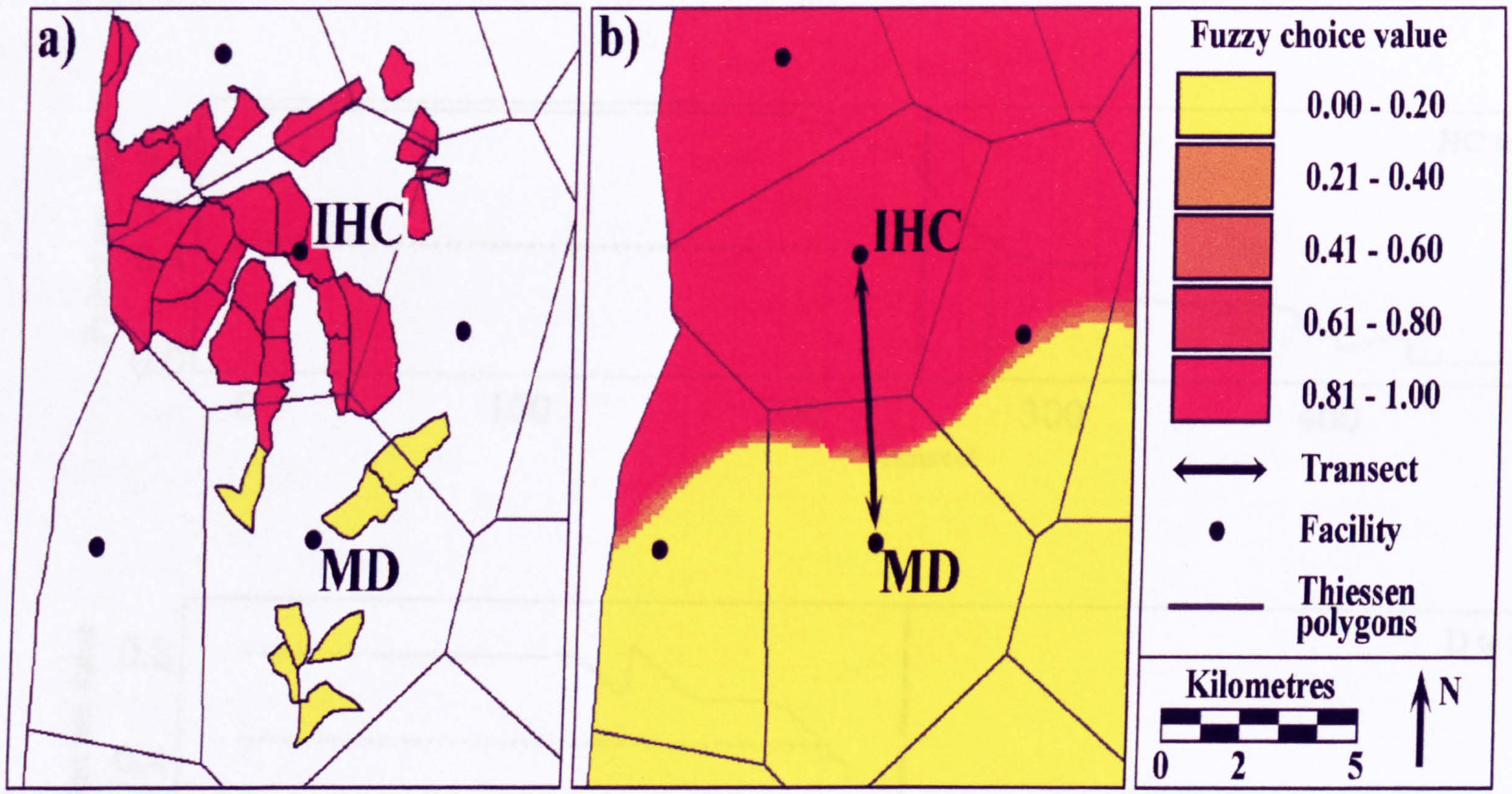
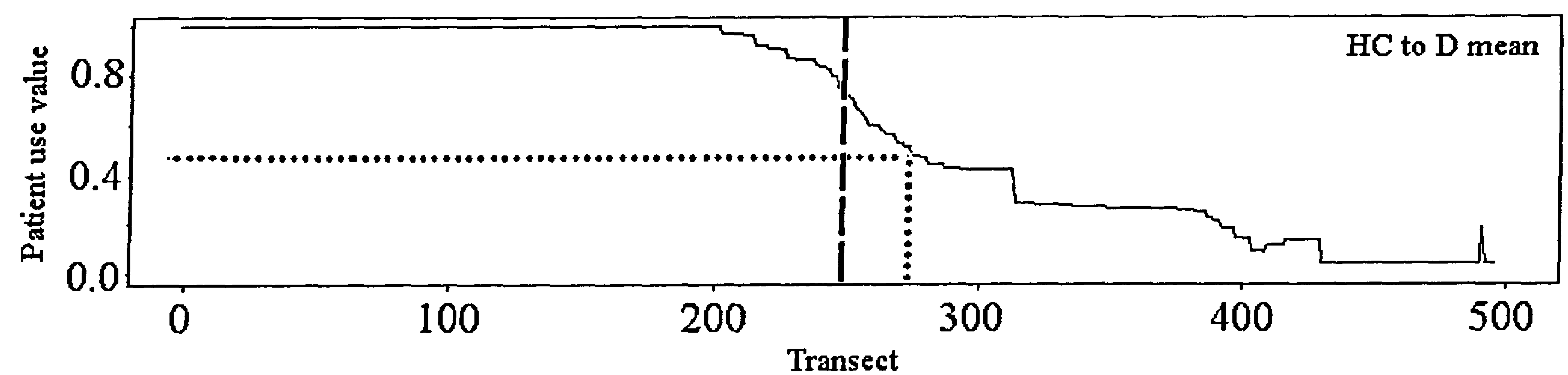
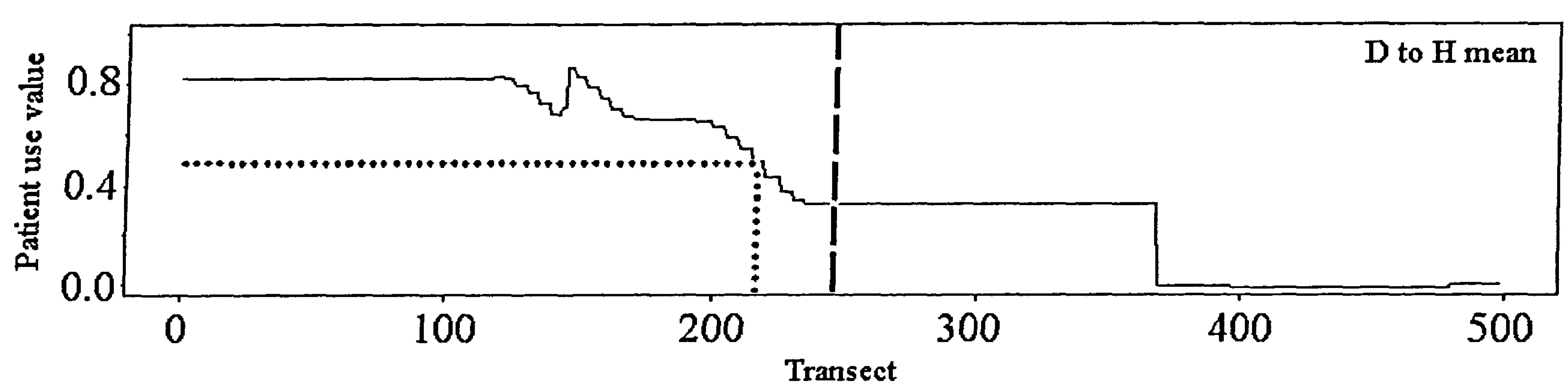


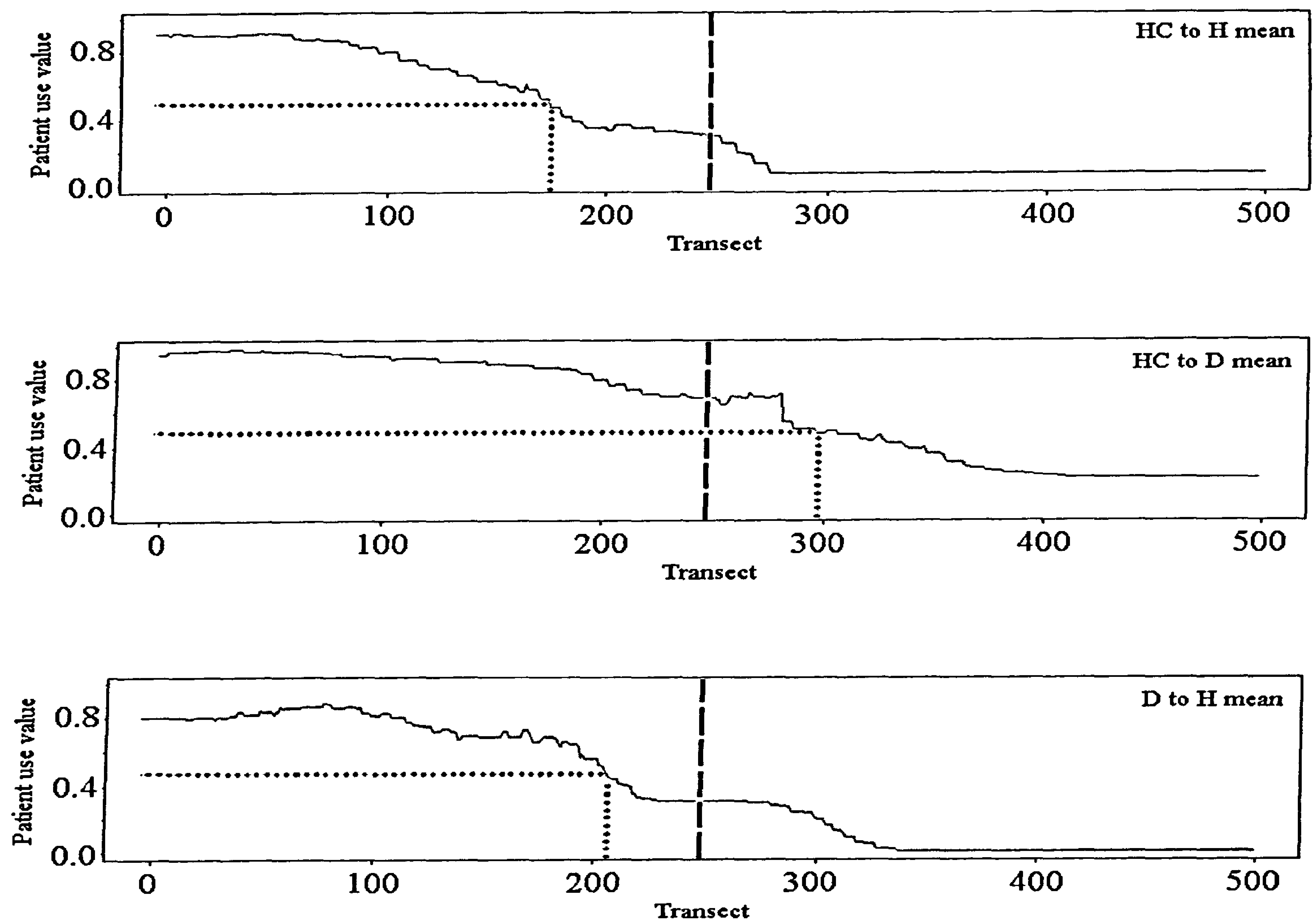
Figure 3.6 a-d Mean fuzzy choice transects for all neighbouring facility pairs in each district of class health centre to dispensary (HC to D), dispensary to hospital (D to H) and health centre to hospital (HC to H) illustrating the relative draw of different facility types. The location of the theoretical Thiessen boundary is marked at the mid-point (dashed line) along with the location of the observed 0.5 fuzzy choice value (doted line)

a) Bondo district

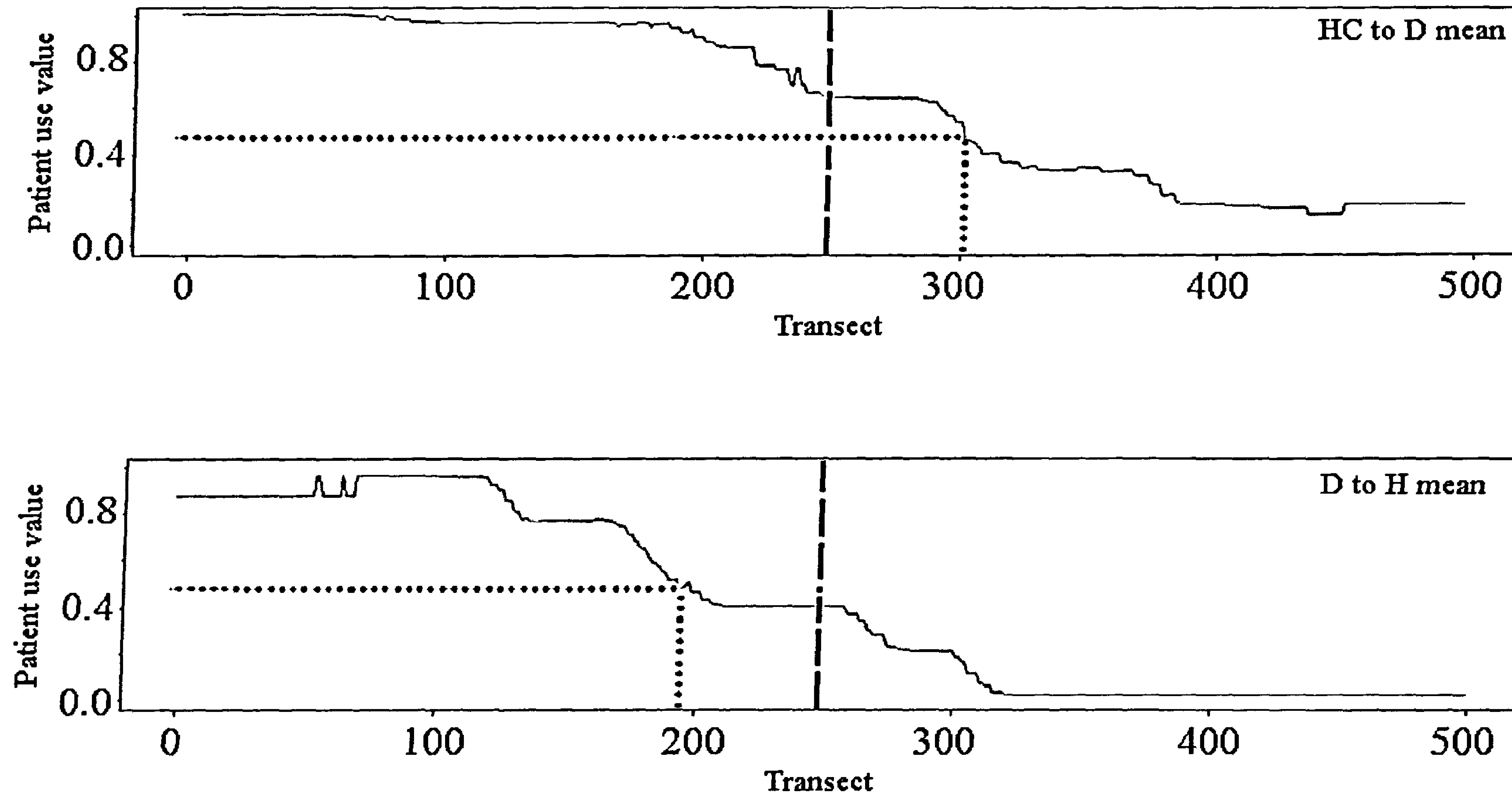




b) Greater Kisii district



c) Kwale district



d) Makueni district

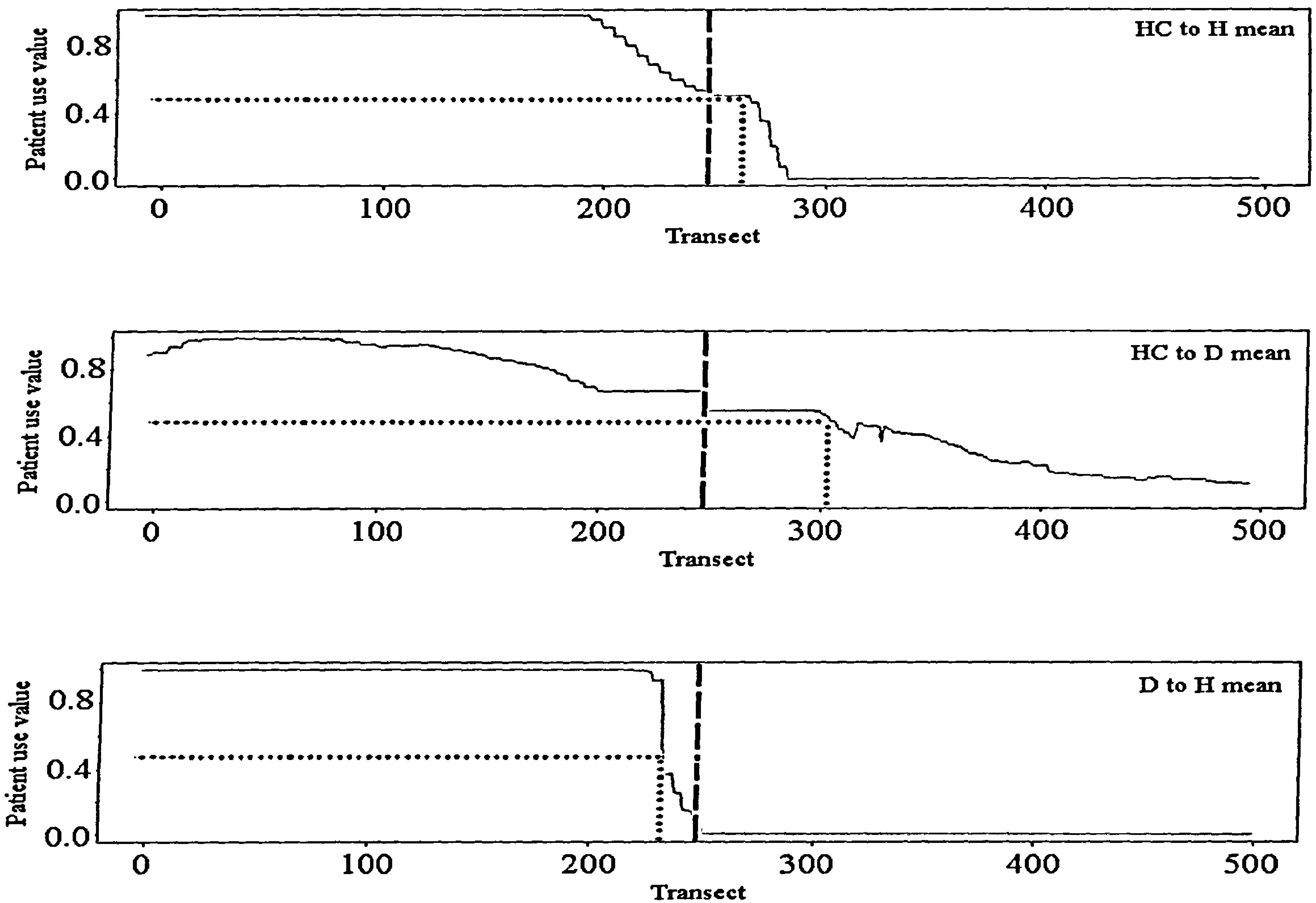
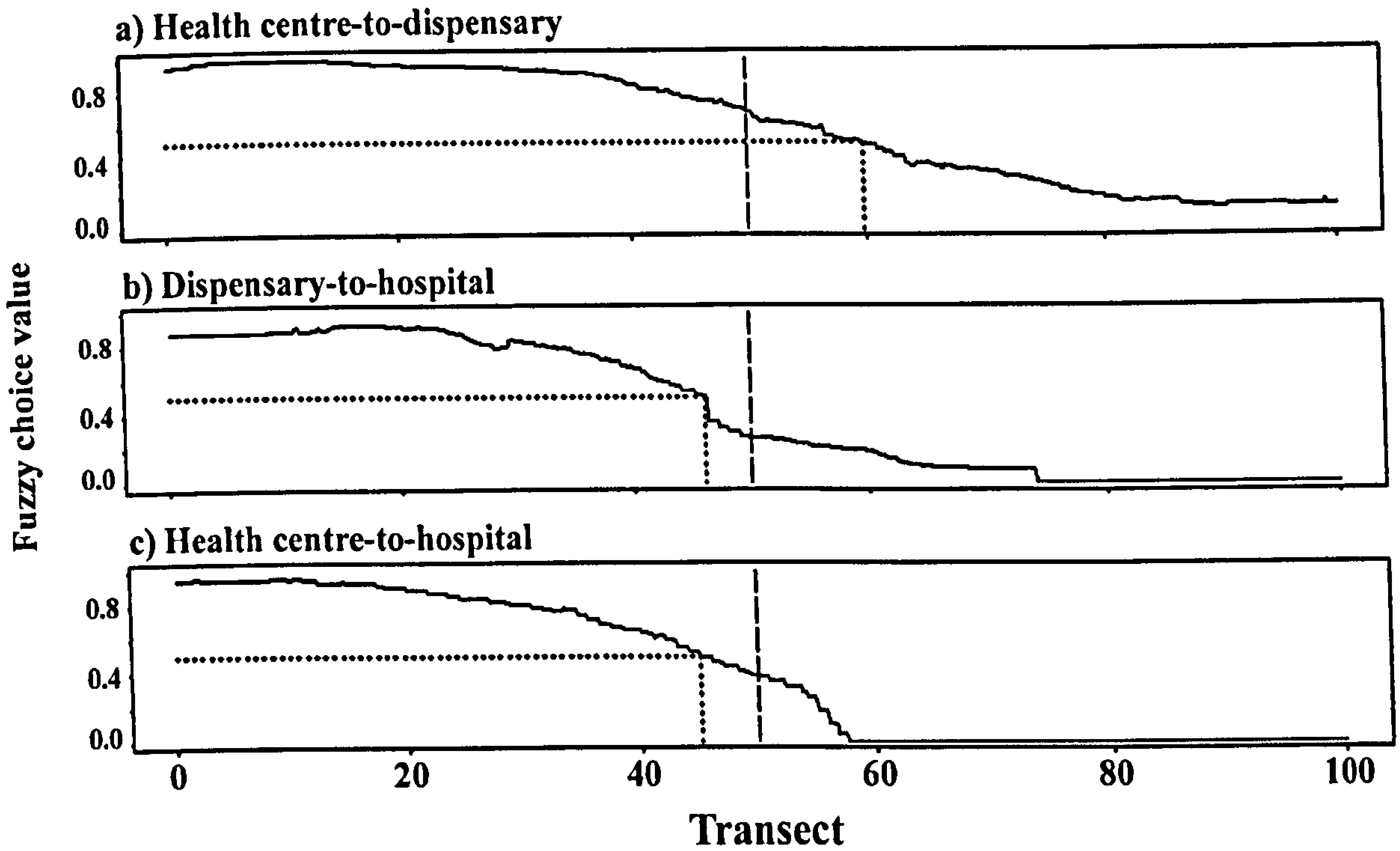


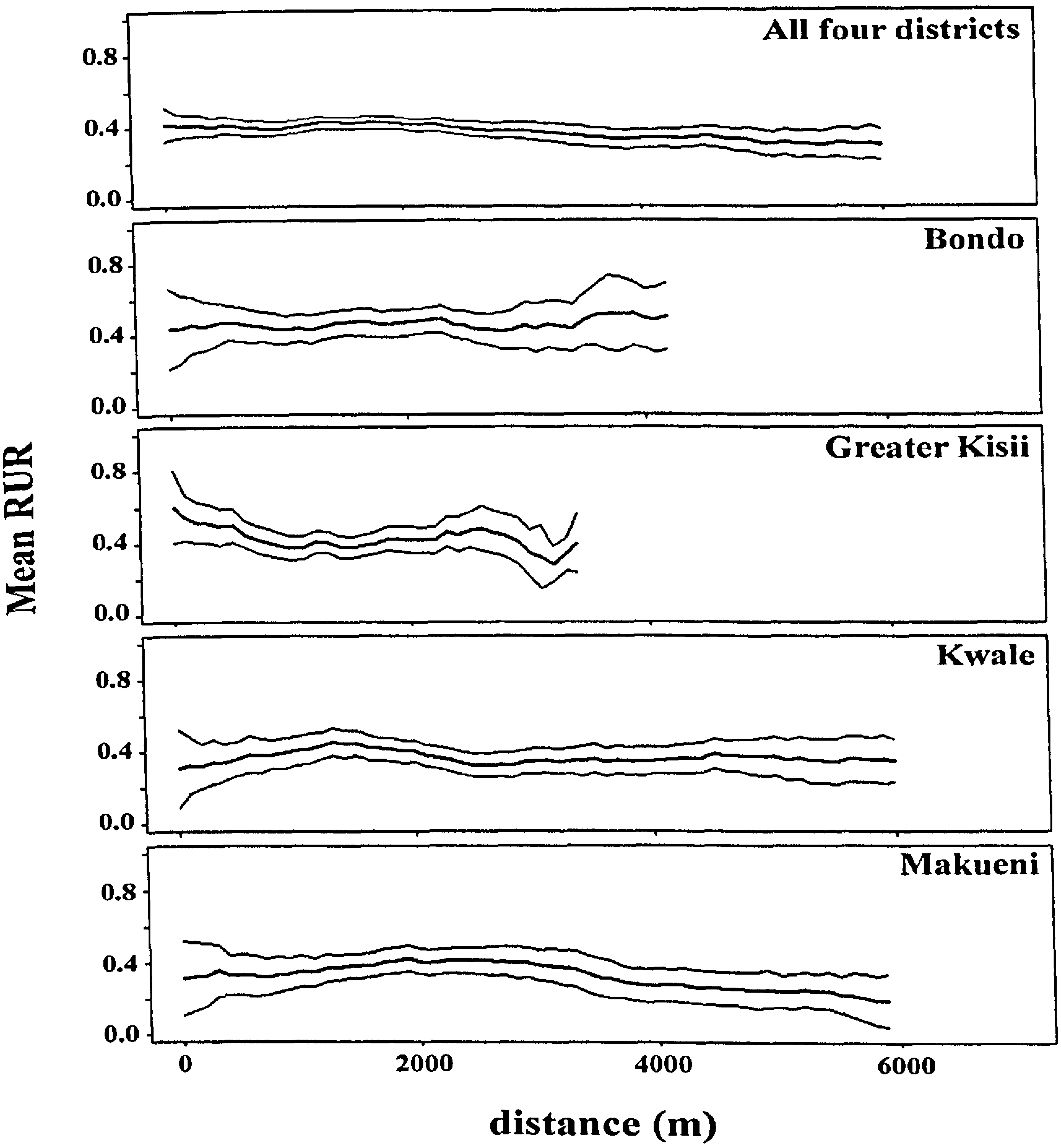
Figure 3.7 Mean fuzzy choice transects for all neighbouring facility pairs of class health centre to dispensary (A), dispensary to hospital (B) and health centre to hospital (C) illustrating the relative draw of different facility types. The location of the theoretical Thiessen boundary is marked at the mid-point (dashed line) along with the location of the observed 0.5 fuzzy choice value (dotted line).



3.4.3.2 Variation of utilisation rate within catchment

Relative Utilisation Rate (RUR) plots are shown in Figure 3.8. These include a mean plot for each district as well as an overall mean. Mean plots are accompanied by 95% confidence intervals. Each of the district plots extends to a different length which corresponds to the most distant non-zero pixels found in any of the study catchments in each district. The districts of Bondo and Greater Kisii are characterised by a relatively dense network of facilities, corresponding to a higher population density. Catchments are, therefore, smaller than some of those found in the more rural Kwale and Makueni districts. For Bondo, RUR fluctuates but exhibits no systematic trend with distance. For Greater Kisii it decreases with distance. For both Kwale and Makueni RUR increases up to around 2 km, and then levels off (Kwale) or steadily declines (Makueni). Overall there exists a slight, but steady decrease in RUR with distance up to 6 km.

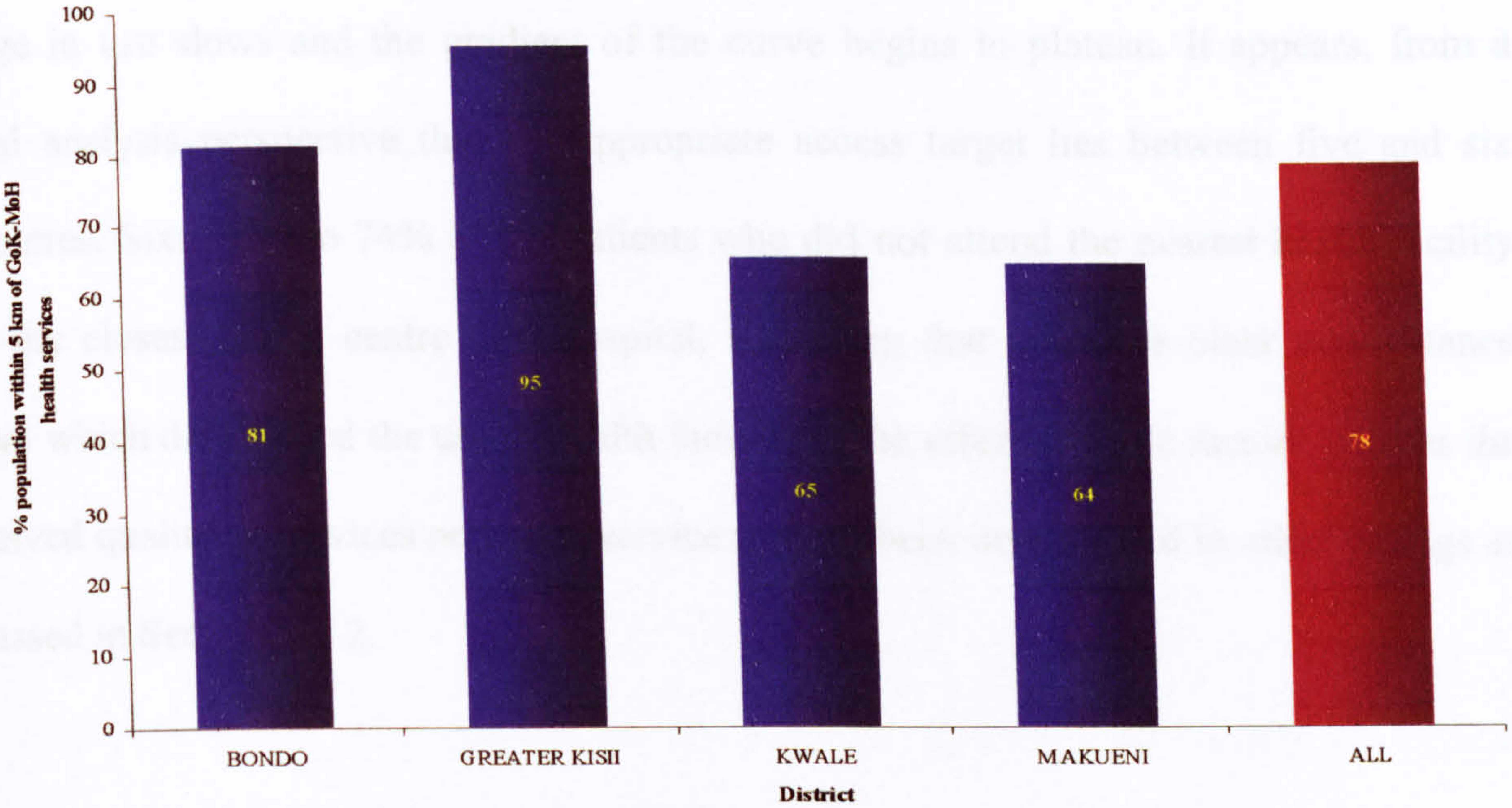
Figure 3.8 Mean overall and district relative utilisation rate (RUR) plots. Thick line shows the mean RUR value of all sampled 100m by 100m grid cells within every study catchment at each given distance. Ninety-five percent confidence intervals are also shown (fine lines).



3.4.3.3 Adjustment of health facility catchments for competition

The results of the transect analysis presented in Section 3.4.3.1 show that where there are two adjacent facilities of different types, the catchment boundary between them shifts in favour of the higher order facility (Table 3.2). In a procedure that will be presented in detail later in Chapter 4, the percentage shift between these boundaries were used as adjustment factors to calibrate the Euclidean distance-only theoretical catchment boundaries developed in Chapter 2. The catchment boundaries adjusted for competition were then used to compute the population within 5 km of GoK-MoH health services. The result showed that 81% of the population in Bondo, 95% in Greater Kisii, 65% in Makueni and 64% in Kwale lived within 5 km of GoK-MoH health services (χ^2=297332.94, 3df, P<0.0001). Overall, 78% of population in the study districts was within the 5 km threshold (Figure 3.9).

Figure 3.9 The proportion of population in the study districts within 5 km of GoK-MoH health services after the Euclidean model was adjusted for competition



3.5 Discussion

The results from the analysis of febrile patients attending Government facilities show that rural populations on average travelled greater distances than urban populations to health facilities, the greatest difference being in Makueni at 5.1 km and smallest in Bondo at 0.7 km. The actual usage analysis of health facilities for the treatment of fevers also showed that 56% or more of the users in all districts attended the nearest government health facility.

Further, the number of patients using a facility decreased as the distance from that facility increased. However, in all districts, use peaked at 2-3 km from health facilities corresponding to the peak in population distribution at this distance. A further possible influence on this trend is that the urban population, who are closest to health services, had an increased ability to access private and other sources of health care. In respect of the 5 km threshold defined as a target in the health sector reform, over 60% of actual users in all the districts attended health facilities within this distance. There was a striking correlation between the theoretical proportion of the population having access to health facilities within 5 km, and the proportion of users attending them at this distance. In addition, Figure 3.2 shows that the five-six-kilometre distance is the point of inflection, where the rate of change in use slows and the gradient of the curve begins to plateau. It appears, from a spatial analysis perspective that the appropriate access target lies between five and six kilometres. Sixty-five to 74% of the patients who did not attend the nearest health facility used the closest health centre or a hospital, indicating that there are other non-distance factors which determined the use of health facilities. The effect of these factors, such as the perceived quality of services on health service use has been investigated in other settings as discussed in Section 1.5.2.

During the second series of analysis, the construction of fuzzy patient choice surfaces presented a more robust means of assessing patient behaviour for two neighbouring health facilities and identifying the location and nature of the catchment boundary between them. This method represents the conversion of two separate facility-based variables (attendance per EA per facility) into a single facility-pair-based variable (fuzzy choice) that describes the spatial partitioning of patients between the two facilities in question. By analysing patient choice along a transect between two neighbouring facilities, the influence of other facilities is minimised. The mean fuzzy choice transects for each transect class (Figure 3.7) suggest a smooth gradient of choice between the two facility types in question. This is not, however, representative of the shape of most of the 78 individual-choice transects. These exhibited a much sharper transition from high to low choice values indicating a crisper boundary. Although this characteristic of the individual plots is smoothed in the averaging process, the mean transects are useful for illustrating the relative drawing power of the different facility types as a whole, especially with reference to the TP boundary. The calculation of mean boundary locations, along with the use of appropriate significance tests (Table 3.2), provides a means of comparing directly the observed behaviour patterns to those assumed in a TP catchment model.

From the data set used in this study, the results suggest that the TP model does not always provide a realistic division of a population into facility catchments when dealing with facilities of different types and that a greater level of model accuracy would be achieved if boundaries were shifted away from the higher-order facility towards the lower-order facility. Whilst these results reveal trends in patient choice between formal sector options, the omission of non-GoK service providers in the analysis means that they must be considered with caution when extrapolated to a wider setting.

The simple allocation of a population into a series of contiguous facility catchments developed through the TP technique assumes that a patient's likelihood of visiting the facility is not affected by their distance from it. The method presented allows the effect of distance on utilisation rate to be studied in isolation from the possible influence of surrounding facilities. Although one consequence of the use of exclusion buffers is that the maximum distance over which this relationship can be studied for any given set of sample facilities is inevitably reduced, it provides a means of elucidating the influence of distance alone. The degree of confidence associated with each of the mean plots in Figure 3.8 follows a similar pattern – wide confidence intervals at small distances, which narrow through medium distances before widening once more at the larger distances. This consistent pattern can be explained largely by changes in sample size. Only those EAs that contributed patients to the sample could be included in the analysis and this represented a relatively sparse sample (between 13% and 28% of EAs across the four districts). The successive 100 m distance bands (over which RUR values were averaged) can be considered as a series of concentric bands of equal width and, as such, their area increases linearly with distance from facility. Distance bands close to the facility are, therefore, smaller and less likely to contain as many non-zero RUR pixels as those further away, with a corresponding effect on sample size. When considering the largest distances in each district the sample size is likely to be small since there are few examples of catchments that extend to this distance.

A general decrease in RUR is evident with distance up to around 6 km. This suggests that, for the data set studied, the assumption of uniform within-catchment utilisation rate is sub-optimal and that the 6-km mark is the distance within which most of the patients using a health facility in the districts come from and is consistent with Figure 3.2. The observed decline with distance is also consistent with most other low-income country studies (Section 1.5.3.3) although it is far less pronounced than many of those reported. A reasonable explanation for this difference is that the influence of neighbouring facilities is often manifested as a reduction in RUR towards the periphery of a catchment and this effect has not been removed adequately in many studies leading to their over-reporting of decline in RUR with distance.

Whilst knowledge of the within-catchment pattern of RUR is vital in the formulation of a modelling strategy it falls some way short of explaining the absolute pattern of facility usage. This shortfall arises because a significant proportion of paediatric fevers are treated outside the formal sector (Amin *et al.*, 2003; Nyamongo, 2002). If, for instance, catchment population estimates made without consideration of this non-attendance are then used as denominators (with facility disease incidence data as numerator) to estimate disease rate, then rates may be under-estimated.

In Kenya malaria case-management is operated at all levels of the health sector and by multiple government and non-government service providers. However, new drug policies, essential drug distribution, regulation and capacity development of health facilities are often limited initially to government service providers (http://www.measuredhs.com). As such this chapter's analysis has focused on only Government health facilities. The importance of other sectors such as the informal shopkeepers, community-based health workers, the private clinical services and those provided by NGO's and Missions is well described (Amin *et al.*, 2003, Nyamongo, 2002).

In summary, analysis in this chapter showed that the location of a catchment boundary between any two neighbouring GoK-MoH health facilities was statistically significantly different from those of the TP technique, particularly when the neighbouring facilities were of different service levels. The catchment boundary between two adjacent facilities tended to shift in favour of the higher-order facility. When the theoretical Euclidean-based catchment boundaries developed in Chapter 2 were adjusted for competition between facilities, the proportion of population within 5 km of GoK-MoH health facilities decreased when compared to that prior to adjustment. This decrease was between 4-6% for the study districts with an overall reduction of 4%. These differences between the two models were statistically significant (χ^2=202124.67, 1df, P<0.0001). Secondly, use of health services for the management of paediatric fevers varied with distance from health facilities, overall and within the facility's catchment. Thirdly, a 6 km distance was found to be a threshold beyond which the use of GoK-MoH services for the treatment of paediatric fevers diminished.

Important as it was in exploring the validity of the principles upon which traditional SA modelling is based, the data used in the analysis in this chapter cannot be used to develop comprehensive spatial accessibility (SA) models as it had several intrinsic limitations. These include the use of Euclidean distances to model access instead of actual transport routes, patients seen at GoK-MoH health facilities mapped only to the village (EA) and not the higher resolution homestead level and lack information on the broad treatment seeking patterns of patients to compute the actual utilisation rate of government health services.

In Chapter 4, high-resolution spatial and community household survey data for the four study districts are used to address the limitations and develop definitive models of GoK-MoH health service access and utilisation. The differences between the Euclidean definition of distance and those based on actual transport network adjusted for the impact of topography and land cover are analysed. The results of the assessment of the TP technique revealed in this chapter are then implemented using household level data on service use.

CHAPTER 4:
Spatial accessibility and utilisation models of Government of Kenya public health services

4.1 Background

The importance of spatial accessibility (SA) to health care to population health is well documented (Section 1.5.3). However, there is a basic problem of lack of satisfactory methodologies of quantifying SA that link the theoretical assumption that people always use the nearest health services, to the actual trends in utilisation of health services. The review of the primary care access models in Section 1.6 showed that the methodologies currently used to measure SA suffer one or more of the following limitations:

1. Patients are assumed to always use the nearest service point and competition between the array of health services are not considered

2. Patient border crossing or overlap between health facilities is often ignored

3. Variations in access or utilisation rates within catchment areas are not accounted for

4. Distance or travel-time thresholds for primary health care seeking are used, but very often these are guessed and not based on any empirical data

5. Often the supply side only is modelled and the consumer or population side is ignored

Exploratory analysis in Chapter 3 showed that the location of a catchment boundary between any two neighbouring GoK-MoH health facilities of different service levels differed highly from those described by the TP technique. Secondly, use of health services for the management of paediatric fevers varied with distance from health facilities, overall and within the facility's catchment. Thirdly, a 6 km distance was found to be the threshold beyond which the use of GoK-MoH services for the treatment of paediatric fevers diminished. However, the data used in the analysis in Chapter 3 could not be used to develop comprehensive SA models as it had several intrinsic limitations. First, Euclidean distances were used to model access instead of actual travel routes. Second, patients seen at the GoK-MoH facilities were mapped to the village (EA) and not the higher resolution homestead level. Finally, to compute the utilisation rate of GoK-MoH health services the proportion of patients using this sector out of all patients at any given interval was necessary and this was not available from the survey data presented in Chapter 3. Improving the resolution of the data to household level and linking it to the transport network, to examine actual use of services for fever management was made possible through a community survey.

A description of the survey methods and data is given in Section 4.2 followed by a brief summary of the community survey data. In Section 4.3 the development of the theoretical spatial models of access to GoK-MoH health services based on four different definitions of distance is described. The differences between the Euclidean model used in Chapters 2 & 3 and the actual transport network models with respect to the proportion of population within 5 km of GoK-MoH health services are investigated. This is then followed by a spatial analysis of community survey patients' choice patterns between any two neighbouring health facilities, resulting in the development of choice probabilities (boundary adjustment factors) for different service types (Section 4.4). In Section 4.5, these choice probabilities are used to adjust the theoretical models developed in Section 4.3 to account for competition between adjacent health facilities. An accuracy assessment of both the adjusted and theoretical models is undertaken to test the reliability of the models and the impact of both the different definitions of distance and the use of adjustment factors. The best-fit model is then selected as the definitive access and use model of GoK-MoH health facilities (Section 4.6). The utilisation rate of GoK-MoH health facilities for the treatment of paediatric fevers, based on the best-fit model, is computed (Section 4.7). Finally, in Section 4.8, the Euclidean models used in Chapter 2 & 3 are compared with the best-fit model developed here with regard to the estimates of general spatial access level to government health services.

4.2 The community household survey of fever treatment

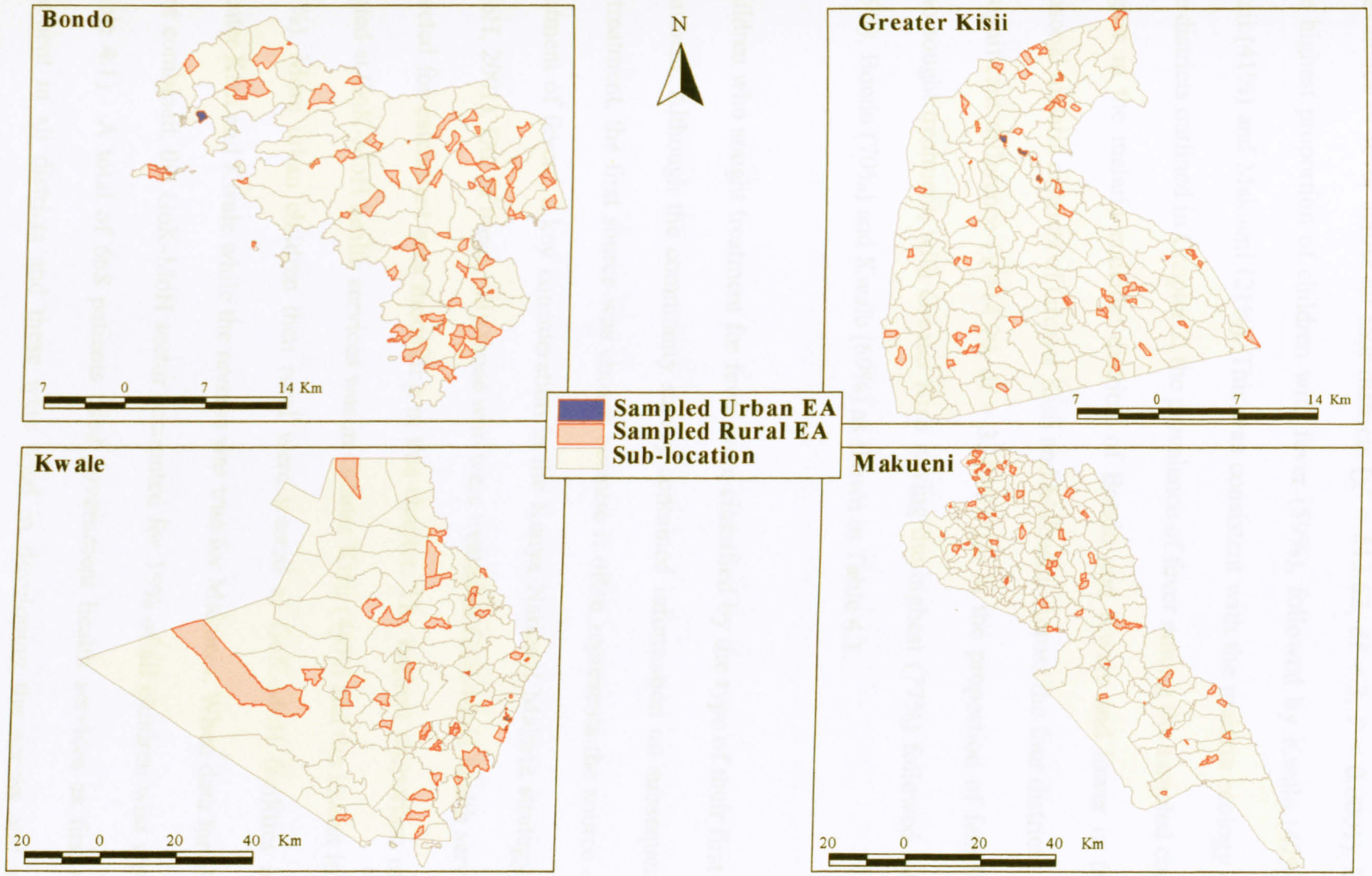
The study was conducted in the four districts (Bondo, Greater Kisii, Kwale and Makueni) described in detail in Section 2.3 and was made up of two main parts. The first part involved developing spatial databases of transport network, elevation, rivers, lakes, parks, forests and all formal health service providers as described in Chapter 2. This provided the basis for conducting the household community survey of febrile children.

In 2001, a stratified random sample of EAs was selected for each district within two strata (urban and rural) to ensure that the sample of EAs reflected the percentage of population within a district classified as urban or rural. Sampling of EAs continued until approximately 25,000 people were included in each district. This sample size was required for a 15%, 20% and 30% increase in the proportion of bednet use by homesteads and children less than 5 years in the study districts over time and was therefore not explicitly designed to address health service utilisation for the management of fevers. Nonetheless, because of the random nature of community sampling and the considerably large sample size it's expected that observations of service use are adequately representative of the population in the districts. Besides, the sample chosen for each district is considerably larger than those selected in the KDHS for a similar population in investigating treatment seeking behaviour (http://www.measuredhs.com). Maps of the sampled EAs for each district are presented in Figure 4.1.

Between December 2001 and January 2002 four teams of 40 trained field staff visited each district to map homesteads in each of the randomly selected EA using a GPS (Garmin etrex, Garmin Ltd., Kansas, US; Trimble, Trimble Navigation Ltd., California, US). High resolution maps of the sampled EA for each district, showing the location of roads, health facilities and shops were then generated using the GIS to help the field staff correctly identify the EA on the ground. Each homestead was assigned a unique identification number comprising the district + sub-location + EA + homestead codes. A questionnaire (Appendix 3) was translated into KiKamba, KiGussi, KiLuo and KiSwahili. The questionnaires were back-translated into English by independent assessors fluent in each language to identify question ambiguities and sensitivities. Questionnaires and survey procedures were piloted before the main survey.

Each homestead was visited and field staff sought informed consent, enumerated the household and completed the questionnaire on the use and access to ITN, intermittent presumptive treatment by women pregnant in the last year (Guyatt *et al.,* 2004) [Appendix 4.1], treatment of fevers in children aged less than five years (Amin *et al.,* 2003) [Appendix 4.2], exposure to malaria awareness materials and whether indoor residual house-spraying had been conducted in the homestead in the last 12 months. Household heads and responsible members of the homestead were asked to report upon the numbers and ages of people usually resident (*de jure*) in the homestead. Where a homestead had children aged less than 5 years the names of these children were obtained. A random selection of one child from names placed in a container was used to identify a single child per homestead for further questioning. Specifically for the present study, mothers or guardians were asked whether the child had suffered from a fever during the preceding 14 days and if the child was still febrile on the day of interview. For all resolved or currently febrile children further questions were asked on whether or not they sought treatment. For those that sought treatment, information on sources of treatment for fever management was obtained. All sources and types of therapy were coded according to a detailed coding list. This list included whether the source of treatment was an informal retail outlet, a government, mission or non-governmental organisation (NGO) health facility and were matched to codes of facilities and outlets created for each district (Sections 2.4.2 & 2.4.3). Data were double entered and verified using Microsoft ® Access 2000 (Microsoft Corp., USA).

Figure 4.1 A map of sub-locations showing the sampled enumeration areas (EAs) in the four study districts used during the community survey



4.2.1 Summary of the community survey data

In the community survey, a total of 6,287 children < 5 years of age were interviewed (1,644 in Bondo, 1,425 in Greater Kisii, 1,627 in Kwale and 1,591 in Makueni). Overall, 42% (2,655) of all sampled children had fever. There was a significant difference in the prevalence of fever across all four districts ($\chi^2 = 513.62$, df = 3, $P < 0.0001$). Bondo had the highest proportion of children with fever (59%), followed by Kwale (47%), Greater Kisii (41%) and Makueni (21%). This was consistent with the malaria ecology of each of the districts outlined in Chapter 2; the prevalence of fever among the sampled children was higher in the malaria endemic districts of Bondo and Kwale and lower in the acutely seasonal malaria districts of Greater Kisii and Makueni. Across the four districts, there was a significant difference (χ^2=14.90, df = 3, P=0.002) in the proportion of febrile children who sought treatment, with Greater Kisii having the highest (77%) followed by Makueni (75%), Bondo (70%) and Kwale (69%) as shown in Table 4.1.

Children who sought treatment for fever were classified by the type of their first source of treatment. Although the community survey contained information on subsequent sources of treatment, the first source was chosen because it often represents the source of prompt treatment of fevers, a key consideration in the Kenya National Malaria strategy (KNMS) (MoH, 2001). Out of these, only those who were treated at GoK-MoH health services were selected for catchment area modelling in this chapter. The highest proportion of children treated at GoK-MoH health services was in Greater Kisii (44%) and the lowest in Makueni (22%). More urban children than rural were treated at GoK-MoH facilities in Bondo, Greater Kisii and Kwale while the reverse was true for Makueni. When data for all districts were combined, the GoK-MoH sector accounted for 35% of all children who were treated (Table 4.1). A total of 668 patients used government health services as first source of treatment in all districts and these were used in developing the access and utilisation models of GoK-MoH health services described in the following sections.

Table 4.1 Number of children <5 yrs classified into those with no fever, with fever but not treated, and fever treated by district

	Bondo (1644)	Greater Kisii (1425)	Kwale (1627)	Makueni (1591)	All districts
	Total	Total	Total	Total	Total
Fever- No Action Number (%)	293 (30)	133 (23)	239 (31)	82 (25)	747 (28)
Fever- Action (all sources) Number (%)	682 (70)	448 (77)	529 (69)	249 (75)	1,908 (72)
Fever- Action (seen at GoK-MoH facilities) Number (%)	219 (32)	198 (44)	201 (38)	56 (22)	668 (35)

4.3 Development of theoretical spatial models of access to GoK-MoH services

4.3.1 Euclidean model (Model 1)

This model, repeated here so it could be compared with other models, was developed in Chapter 3 using the TP technique (ArcView 3.2, 1992-1999, ESRI Inc.). Catchment areas for each GoK-MoH health facility in the four districts were generated. This technique assigned each point on the map to the nearest health facility based on straight-line or Euclidean distances, and is henceforth referred to as Model 1. The time to nearest GoK-MoH health facility was calculated using the *Find Distance* module in ArcView 3.2 GIS with the Spatial Analyst loaded. The output was computed in km but was converted into hours using travel speed of 5 km/h, equivalent to that on the road (Table 4.2).

4.3.2 Non-Euclidean models

The assumption made in the Euclidean model, that people travel on straight lines to health facilities is not a realistic reflection of people's movement patterns. The models presented in Sections 4.3.2.2-4.3.2.4 are based on movement on the actual transport networks adjusted for the influence of topography and other natural barriers. They are based on pedestrian movement only, since results from the community survey showed that > 80% of the patients did not incur transport costs and this was considered to be an indication that most people in the districts walked to health facilities. Models incorporating vehicular speed for the few who used mechanised transport required information on the type of vehicles, travel schedule, speed etc. which was beyond the scope of this study. Whilst roads used in the analysis were classified by type and statutory speed limitations, using these to define real-time vehicular speed, particularly where traffic is not regulated, is likely to overestimate the time required to move from one point to the next. As such analysis for vehicular travel was ignored and all patients were assumed to have walked to the source of treatment.

The non-Euclidean models were implemented using a shortest-path algorithm based on the Naismith-Langmuir rule on pedestrian travel (Langmuir, 1984). Naismith was a founder of the Scottish Mountaineering Club and his rule is still used to obtain a rough estimate of the time required for expeditions. The basic rule of Naismith states that a walker can maintain a speed of 5 km/h on level ground, but 1 hour needs to be added for every 600 m of ascent. It is thought that the rule gives a reasonable minimum time, but was considered optimistic for regular walking. Several refinements have been made to this rule (Aitken, 1977, Langmuir 1984, Wilderness Tech Tips, 1998, Fritz *et al.*, 2000). The Naismith-Langmuir rule, with modifications as shown in Table 4.2, was used to calculate travel speed and develop a shortest path algorithm (coded in C++) for the present study.

Table 4.2 Travel on different terrains based on a modification of Naismith-Langmuir rule

	Naismith/Langmuir rule
Flat (Road)	1.2 minutes per 100 m (5 km/h)
Flat (Off-Road)	2.4 minute per 100 m (2.5 km/h)
Ascents	+ 0.1 minutes per 1m ascent (+1hr per 600 m)
Moderate descents (-5° to –12°)	- 0.03 minutes per 1m descent (- 10mins per 300 m)
Steep descents (steeper than –12°)	+ 0.03 minutes per 1m descent) (+ 10mins per 300 m)

4.3.2.1 The JOURNEY-TIME algorithm

Barriers such as rivers, forests and parks were masked out by assigning a value 9999 to the relevant grid cells. However, where a road traversed such a river or other waterbodies, the road was given precedent and a road speed assigned to the portion covered by the road. This algorithm, henceforth referred to as JOURNEY-TIME algorithm, required an input grid which listed an impedance (travel speed) value for every pixel. The impedance was dependent on the nature of the pixel in question (e.g. road, non-road, swamp etc) and represented the time in minutes taken to traverse a single pixel from side-to-side or diagonally. For example, if average walking speed along a road was taken as 5 km/h, then the impedance value for a road pixel of size 100 m by 100 m is 1.2 minutes. The code also required a DEM, which listed the elevation above sea level of each pixel. When movements between pixels were considered, the gradient associated with this movement was calculated from the DEM. The Naismith-Langmuir rule was then implemented to estimate the effect of gradient on the journey time between the two pixels in question. Direction of slope and gradient were first considered away from the health facility but since the distance from population points to the nearest health facility was of interest, ascent from the facility was computed as descent and *vice versa*.

The JOURNEY-TIME algorithm used an iterative region-growing approach in which each iteration represented a unit of time (currently set to 0.05 minutes – 3 seconds). Each pixel containing a health facility was taken as a seed pixel around which regions of assigned pixels were grown. The first iteration reached all un-assigned pixels that were contiguous neighbours of the seed pixels. When a pixel was first "reached" it required a certain number of iterations before it was considered "traversed". If a pixel had a total impedance of 1.2 minutes, for example, then it required 24 iterations of 0.05 minutes each from when it was first reached before it was considered traversed. As soon as a pixel was traversed it was allocated a journey time value derived from the number of iterations that had been completed at that point.

By progressing the algorithm in short units of time, only allowing new pixels to be considered once they have been reached by other pixels, and calculating gradient for each potential pixel transition, it was possible to ensure that only the fastest route to a given pixel was ever used to calculate journey time. The various models implemented using the JOURNEY-TIME algorithm are described in following sections.

4.3.2.2 Transport network model (Model 2)

The network model measured accessibility to health services based on movement on the transport network only. The inputs required were ASCII format arrays of raster grid maps of health facilities, road network and EA population maps at 100 m x 100 m spatial resolution pixels. These were generated in ArcView GIS (Version 3.2, 1992-1999, ESRI Inc). Every pixel on the road was assigned a speed of 1.2 minutes every 100 m and 2.4 minutes to those not on the road.

4.3.2.3 Transport network-elevation model (Model 3)

The relief of an area, represented by change in elevation, has been recognised to influence not only people's settlement patterns but also their movement within the area (Lin *et al.*, 1999). To account for effect of change in elevation on people's movement on the road network, the DEM was used to generate information on slope variation within the districts. The program converted the elevation values of each point to slope. Since travel on the road was considered from the population-to-facility points, ascent and descent were computed in that direction. With the population point as the base, the increase or decrease in elevation between points was assigned a value of travel time equivalent to change in distance due to change in elevation using the criteria described in the Naismith-Langmuir rule.

4.3.2.4 Transport network-elevation-land cover/use model (Model 4)

To account for land-use/land-cover factors that influence people's movement, raster grids of 100 x 100m resolution pixels of the roads, footpaths, rivers, lakes, swamps, forest and parks were converted into ASCII arrays using ArcView GIS (Version 3.2, 1992-1999, ESRI Inc). Where routes traversed these barriers the travel speed remained unchanged as it was assumed that there was uninterrupted movement across the barrier. Where roads did not traverse these barriers, a mask was implemented so that they were output as areas where it was impossible for pedestrian travel. All the data arrays were then exported in the JOURNEY-TIME algorithm for processing.

4.3.3 Summary of models' data input and definitions

Table 4.3 shows a summary of the data input required for each theoretical spatial access model and the associated definition of distance

Table 4.3 A summary and definitions of the theoretical spatial access models

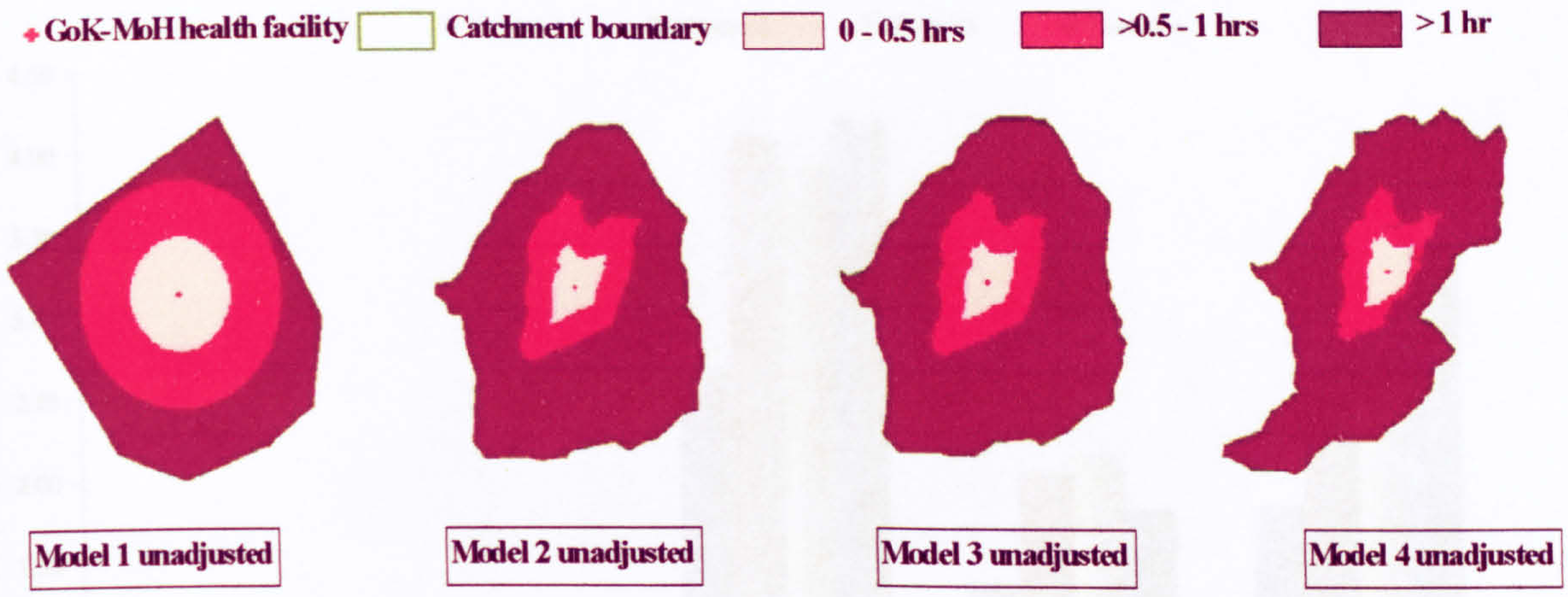
	Spatial data input	**Definition of distance**
Model 1	Health services and EA level population distribution	Euclidean (straight-line) between location of population and health services
Model 2	Health services, EA level population distribution and transport network	Pedestrian movement on the transport network between location of population and health services
Model 3	Health services, EA level population distribution, transport network and elevation	Pedestrian movement on the transport network between location of population and health services adjusted for the effect of slope
Model 4	Health services, EA level population distribution, transport network, elevation, water features and gazetted areas	Pedestrian movement on the transport network between location of population and health services adjusted for the effect of barriers such as slope, rivers, lakes and gazetted areas

4.3.4 Output of the theoretical spatial access models

For each non-Euclidean model (Models 2-4), the JOURNEY-TIME algorithm produced two main outputs: a) where each pixel in an array was assigned the nearest GoK-MoH health facility; and b) where each pixel was assigned a value of travel time to nearest health facility in minutes, which was then converted into hours. The arrays were then imported back into ArcView 3.2 as raster grid maps of 100 x 100 m pixel resolution. The nearest facility raster maps were then converted to vector format to generate polygons representing catchment areas. As an example, the catchment area and travel time surfaces for the four models for a health facility in Kwale are shown in Figures 4.2 and 4.3 respectively. There was a distinct change in the catchment boundary as the input into the models increased in complexity. The median of travel times to the GoK-MoH health services for each district resulting from each model were computed. These models, which are still based on the assumption that people always use the nearest health facility, are henceforth refered to as 'unadjusted' models.

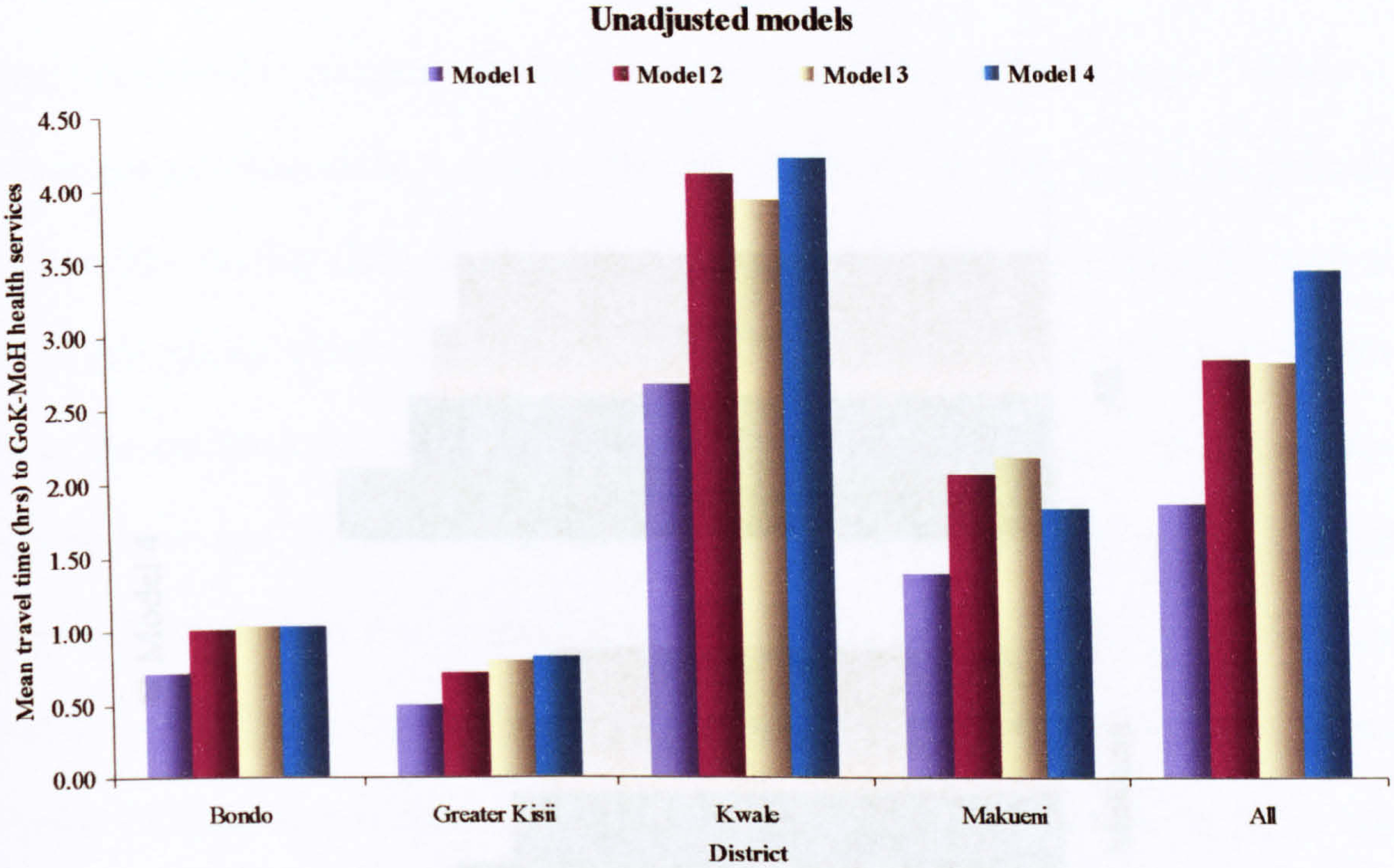
Figure 4.2 A map showing catchment areas around Mwaluphamba dispensary in Kwale based on the four different theoretical unadjusted models

Figure 4.3 A map of travel time to the health facility in Figure 4.2 based on the four different theoretical unadjusted models (Model 1= Euclidean, Model 2=Transport network, Model 3= Transport network and elevation, Model 4=Transport network, elevation and land cover/use).



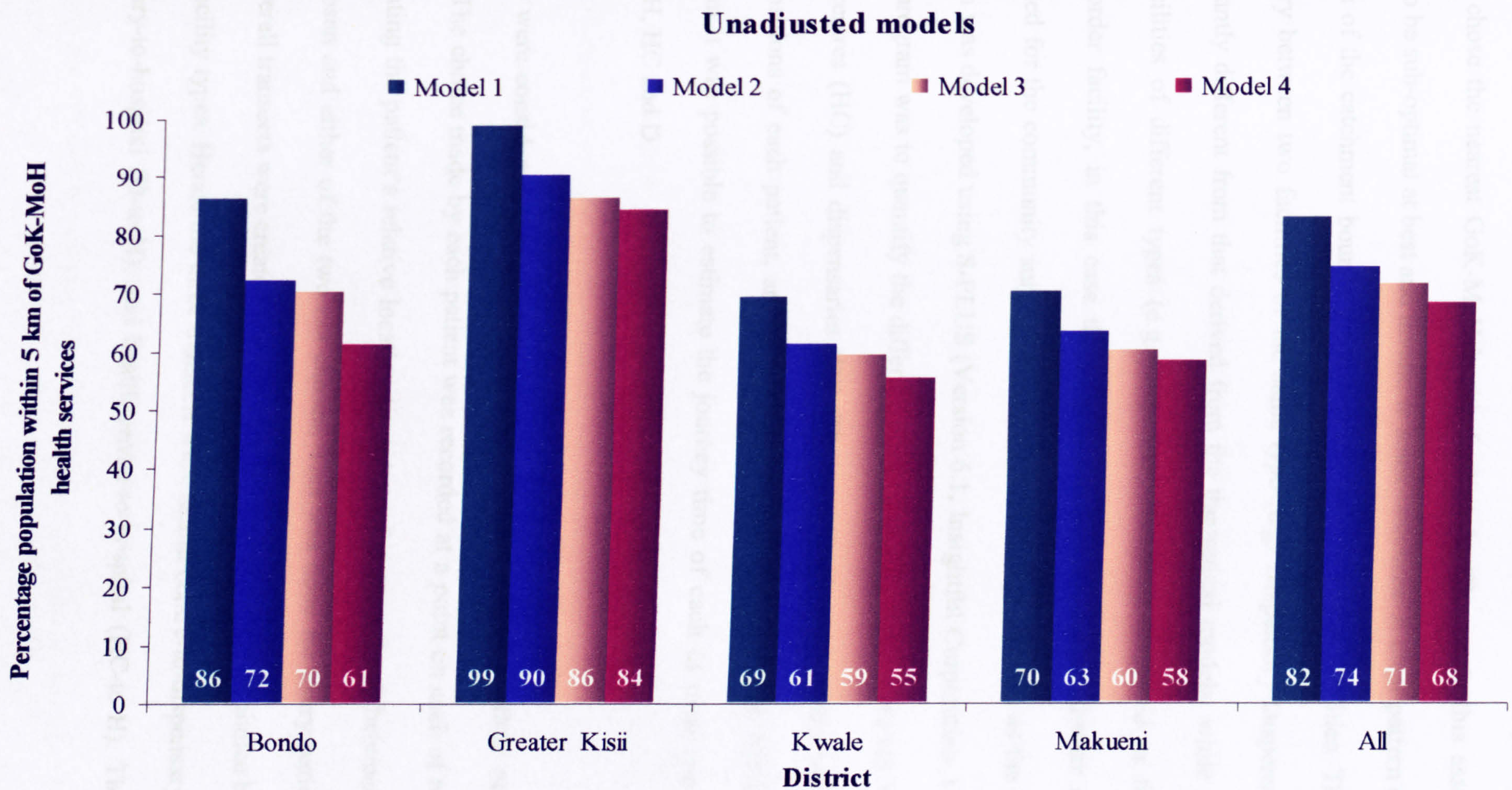
As the input information used in the iterative models increased, the overall level of access to health facilities reduced. For instance in Figure 4.3, the proportion of area within 1 hour of the health facility for Model 1 was more than twice that of the more sophisticated Model 4. This is further confirmed in Figure 4.4, which shows the differences between the four theoretical spatial models (Section 4.3.2.2-4.3.2.4) in the mean of travel times to the nearest GoK-MoH health services. In all the districts, the mean travel time as a result of Model 1 was substantially lower than that of Models 2, 3 & 4. The differences in mean travel time from Models 2-4 were marginal in Bondo and Greater Kisii and substantial in Kwale and Makueni. Overall, Model 4 assigned the highest mean travel times to GoK-MoH health services at any point in the districts.

Figure 4.4 A graph showing mean travel time to nearest GoK-MoH health facilities in the four study districts based on the four theoretical models



The proportion of population in each district within 5 km (the government health access development target) of GoK-MoH health services were computed for each theoretical model (Figure 4.5). The less sophisticated Euclidean model (Model 1) used in Chapters 2 & 3, assigned between 14% in Kwale and 25% more people in Bondo to be within 5 km of GoK-MoH health services than the higher resolution data input model (Model 4). Between the models based on the transport network (Models 2-4) the smallest difference was between Model 2 (transport network only) and Model 3 (transport network + elevation) with the former assigning between 2-3% more people to the 5-km threshold. Further, Model 4 assigned between 4-11% less people to within 5 km of GoK-MoH health services than Models 2 & 3. When data for all districts were combined, the Euclidean model assigned 16% more people to within 5 km compared to Model 4. In summary, the proportion of population within the 5-km threshold decreased as the sophistication of the model increased with a significant difference between the Euclidean model and the high-resolution data input model.

Figure 4.5 A graph showing the percentage of population within 1 hr (~5 km) to the nearest GoK-MoH health facilities resulting from each theoretical unadjusted model for the study districts



4.4 Generating model adjustment factors for discrete and overlapping boundaries based on community-survey data

The models described in Section 4.3 were based on four different definitions of distance, but were essentially theoretical, i.e. they were all based on the assumption that patients always chose the nearest GoK-MoH health facility. In Chapter 3, this assumption was found to be sub-optimal at best and invalid in some instances. A clear pattern existed in the position of the catchment boundary between any pair of health facilities. The catchment boundary between two facilities of the same type (e.g. Dispensary-Dispensary) was not significantly different from that derived from the theoretical models, while that between two facilities of different types (e.g. Dispensary-Hospital) displaced in favour of the higher-order facility, in this case the hospital. In this section, a similar analysis was conducted for the community survey. A script, henceforth referred to as the TRANSECT program was developed using S-PLUS (Version 6.1, Insightful Corporation, UK). The aim of this program was to quantify the differing draw of facility types (between hospitals (H), health centres (HC) and dispensaries (D)). The community-survey data set consisted of point-positions of each patient, and their choice of facility. Using the JOURNEY-TIME algorithm it was possible to estimate the journey time of each of these patients to their nearest H, HC and D.

Patients were considered to have made a three-way choice between their nearest H, HC and D. The choice made by each patient was recorded at a point on each of two transects, representing the patient's relative location (in terms of journey time) between the facility type chosen and either of the two not chosen. This was done for every patient such that three overall transects were created that recorded the spatial pattern of choice between each of the facility types. Hence the three transects were health centre-to-dispensary (HC-to-D), dispensary-to-hospital (D-to-H), and health-centre-to-hospital (HC-to-H). The reverse of each of these pairs was not considered separately as they were simply the inverse of these three.

Each transect was divided into 100 equal and discrete sections and in each section a 'patient choice' value was calculated. This was simply the proportion of total patients recorded in each section who chose the first facility in the pair e.g. D-H, such that a value of 1 indicates all patients attended facility D and a value of zero that they all attended H. Plots of patient choice were then constructed along each transect. The position along the transect where the probability of choosing either of the facilities in a pair was 0.5 was taken to represent the location of the mean choice-boundary between the two facility types. The algorithm also generated the limits of the 95% confidence interval around the line of the facility choice. Since the boundary between a pair of facilities was within the 95% CI, then the limits of this interval encapsulated the overlap area between the two facilities and accounted for cross-border use.

4.4.1 Competition between health facilities of different types

The output of the TRANSECT algorithm were three graphs showing patterns of patients choice of service between HC-D, D-H and HC-H respectively. In addition, the limits of the 95% confidence around the graph of service choice were produced. Figure 4.6 represents the unsmoothed version of these graphs while Figure 4.7 shows the graphs after a moving average window of 10 patient choice intervals was applied.

The X-axes of the graphs represent 100 relative and equal divisions on the transect between HC-D, D-H and HC-H respectively. The Y-axes represent the probability of service choice at every interval in each pair of relationship. The boundary between any pair was the point on the X-axis which corresponded to a probability value of 0.5 on the Y-axis. The graphs showed that boundaries between HCs and Ds in the study districts were shared

58-42 % in favour of the HC. For the D-H and HC-H relationships, these were 40-60 % and 46-54 % respectively, all in favour of the higher order facility, that is, the hospital.

Figure 4.6 Un-smoothed graphs showing the pattern of patients' choice of health services in a HC-D, D-H and HC-H relationship

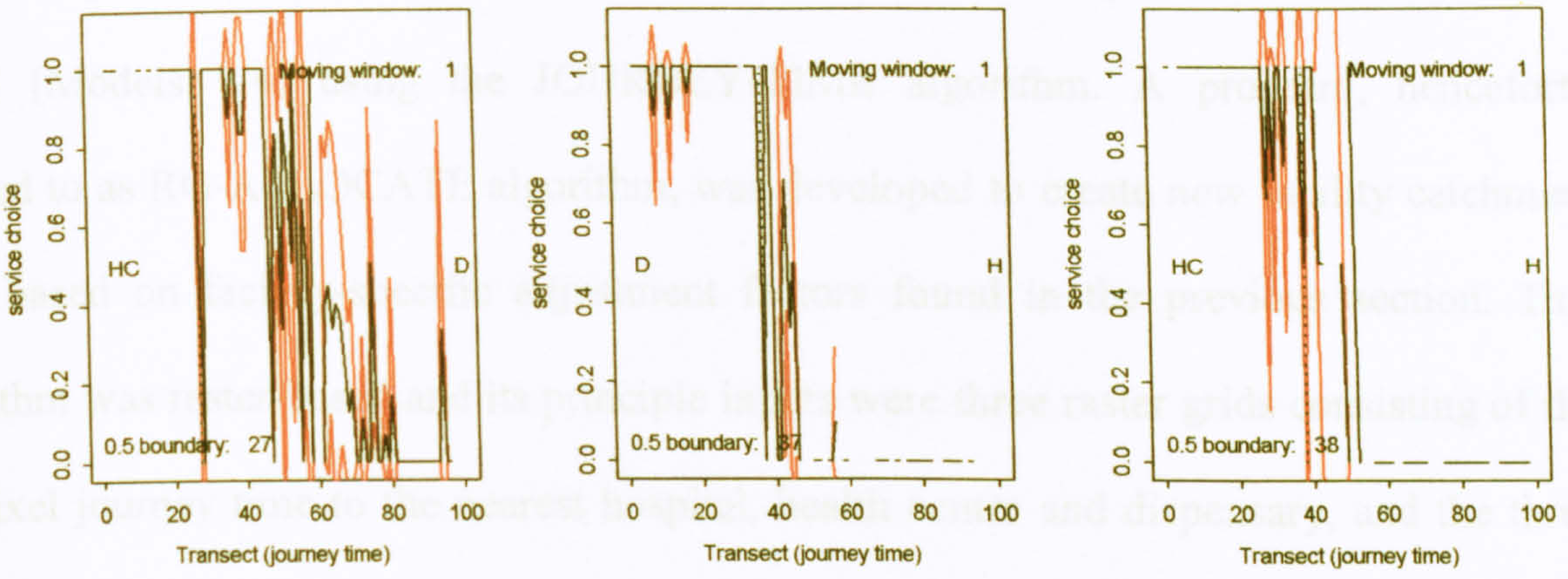
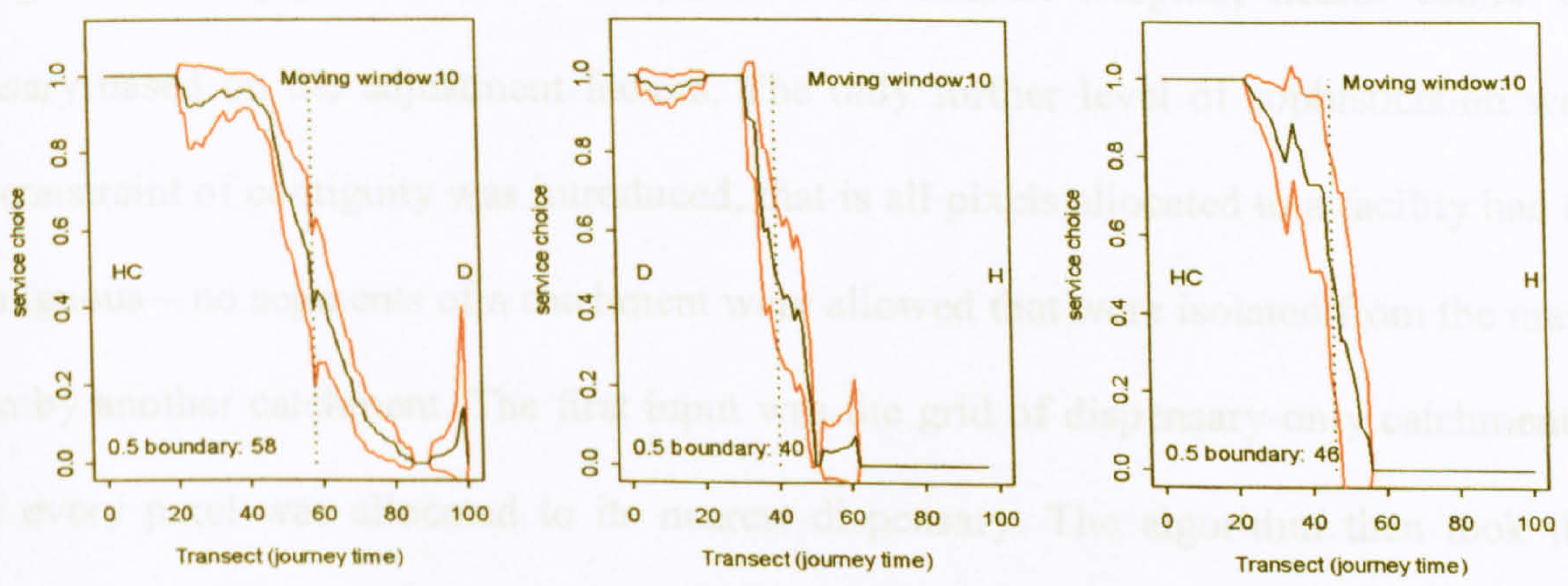


Figure 4.7 Graphs showing the pattern of patients' choice of health services in a HC-D, D-H and HC-H relationship. The graphs were smoothed using a window of moving average of 10 patient choice intervals. The black line plots the patient's choice between any pair of relationship. The red lines represent the limits of the 95% confidence interval, which give the extents of the overlap area. The position on the Y-axis corresponding to a value of 0.5 on the X-axis provides the boundary displacement factor



4.5 Adjustment of theoretical models using the facility choice factors obtained from the community survey

The patients' service choice analysis in Section 4.4 showed that where there was a D-H, HC-H and D-HC relationship, the catchment boundary was displaced in favour of the facility of higher order. Where the relationship was between facilities of type, the displacement was negligible. These adjustment factors needed to be applied to the theoretical models described in Section 4.3, so that the models could be calibrated for actual use of GoK-MoH health services. For each point in the district, the distances to the nearest dispensary, health centre and hospital in turn, were computed for each theoretical model (Models 1-4) using the JOURNEY-TIME algorithm. A program, henceforth referred to as RG-ALLOCATE algorithm, was developed to create new facility catchment areas based on facility-specific adjustment factors found in the previous section. This algorithm was raster-based and its principle inputs were three raster grids consisting of the per-pixel journey time to the nearest hospital, health centre and dispensary, and the three corresponding origin (facility ID) grids. The longitudes and latitudes of all facilities were also required, along with the between-facility adjustment factors (for D-H, D-HC and HC-H).

The algorithm simply allocated each pixel to its nearest hospital, health centre or dispensary based on the adjustment factors. The only further level of sophistication was that a constraint of contiguity was introduced, that is all pixels allocated to a facility had to be contiguous – no segments of a catchment were allowed that were isolated from the main section by another catchment. The first input was the grid of dispensary-only catchments, where every pixel was allocated to its nearest dispensary. The algorithm then took the location of every health centre as the seed in an iterative region-growing function. In the first iteration all pixels that directly neighboured the seeds were considered. The journey-time-to-health-centre value was checked against the journey-time-to-dispensary value with reference to the D-HC adjustment factor. If the value was below the threshold, the allocation remained the same (to dispensary), if it was above then it was re-allocated to the health centre. This process was then repeated for the second and subsequent iterations, each time considering the new neighbouring pixels until the entire grid had been checked.

At this point every pixel was allocated to either its nearest dispensary or health centre. The process was then repeated using this new dispensary/health centre grid as input and the locations of all hospitals as the seed pixels. The processes were identical except, when considering each pixel, a different adjustment factor was considered depending on whether the input allocation was to dispensary (in which case the D-H factor is used) or to health centre (in which case the HC-H factor was used).

When a pixel was allocated to H, HC or D, it received the corresponding facility ID and journey time values from the input grids. A similar process can be applied using the 95% CI adjustment factors to define the facility catchment overlap area.

4.5.1 The effect of adjusting the theoretical models for competition between health facilities

The boundary displacement factors between GoK-MoH health facilities described in the previous section were used in the RG-ALLOCATE algorithm to adjust the four theoretical models described in Section 4.3. These adjustment factors were based on the likelihood of patients using any pair of adjacent GoK-MoH health facilities. An example of the result, comparing the catchment areas of a single health facility from the four adjusted and four un-adjusted models is shown in Figure 4.8. This showed that there were sharp differences in the catchment boundaries between the adjusted and the un-adjusted models.

Comparisons of the four adjusted models for Bondo and Greater Kisii showed that the mean travel time as a result of the adjusted Model 1 remained lower even after adjustment than that of Models 2-4, implying that it assigned higher spatial access values than the latter (Figure 4.9). However, In Kwale and Makueni, the mean travel time for Model 1, which was the lowest before the adjustment, was the highest after adjustment. Detailed comparisons of mean travel times within each district between the adjusted and unadjusted models are shown in Figures 4.10a-d. In Bondo and Greater Kisii, there were no major differences between the adjusted and the un-adjusted models in the mean travel time. In Kwale the mean travel time for Model 1 was higher after adjustment than that of Models 2-4.

Figure 4.8 Map comparing catchment areas derived from adjusted and un-adjusted models for a GoK-MoH health facility (Kisii district hospital in Greater Kisii district)

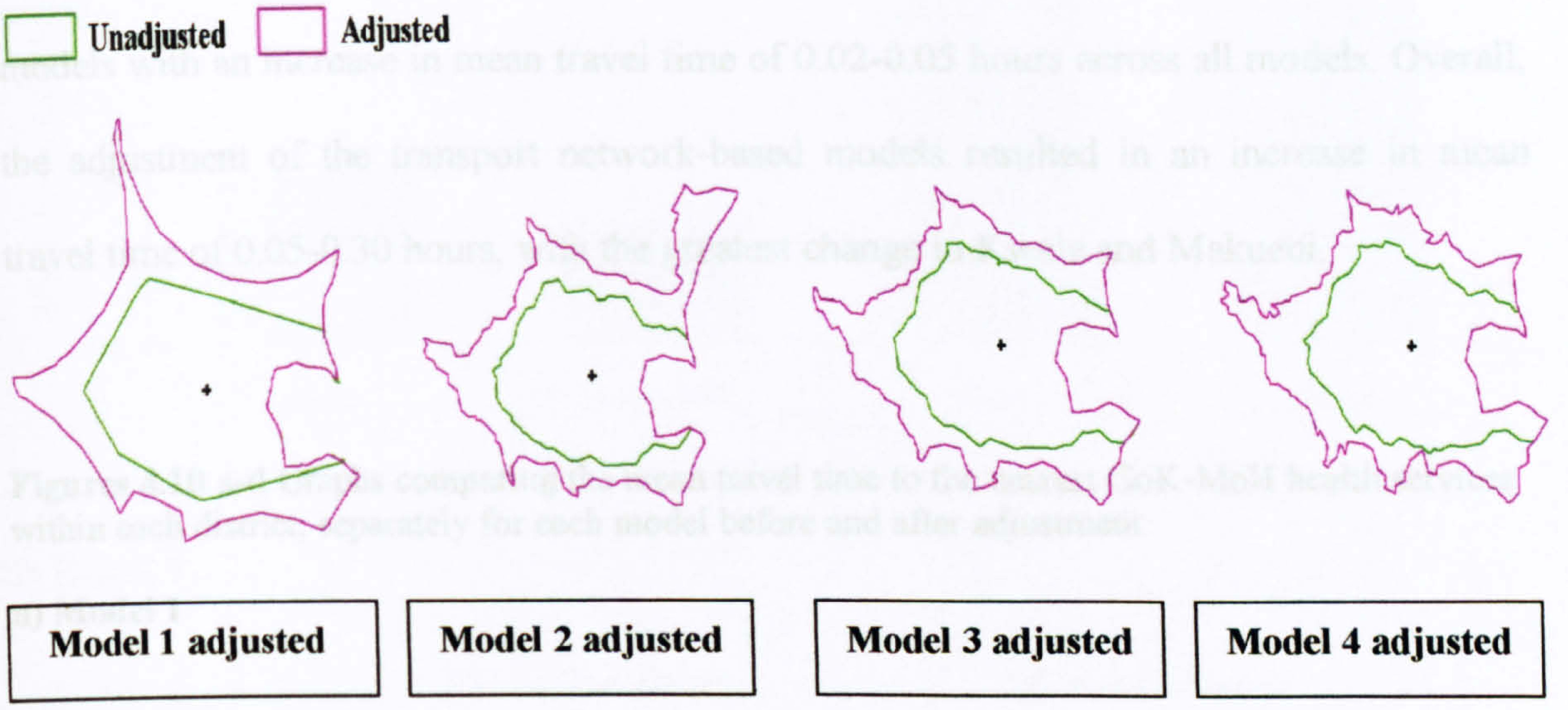
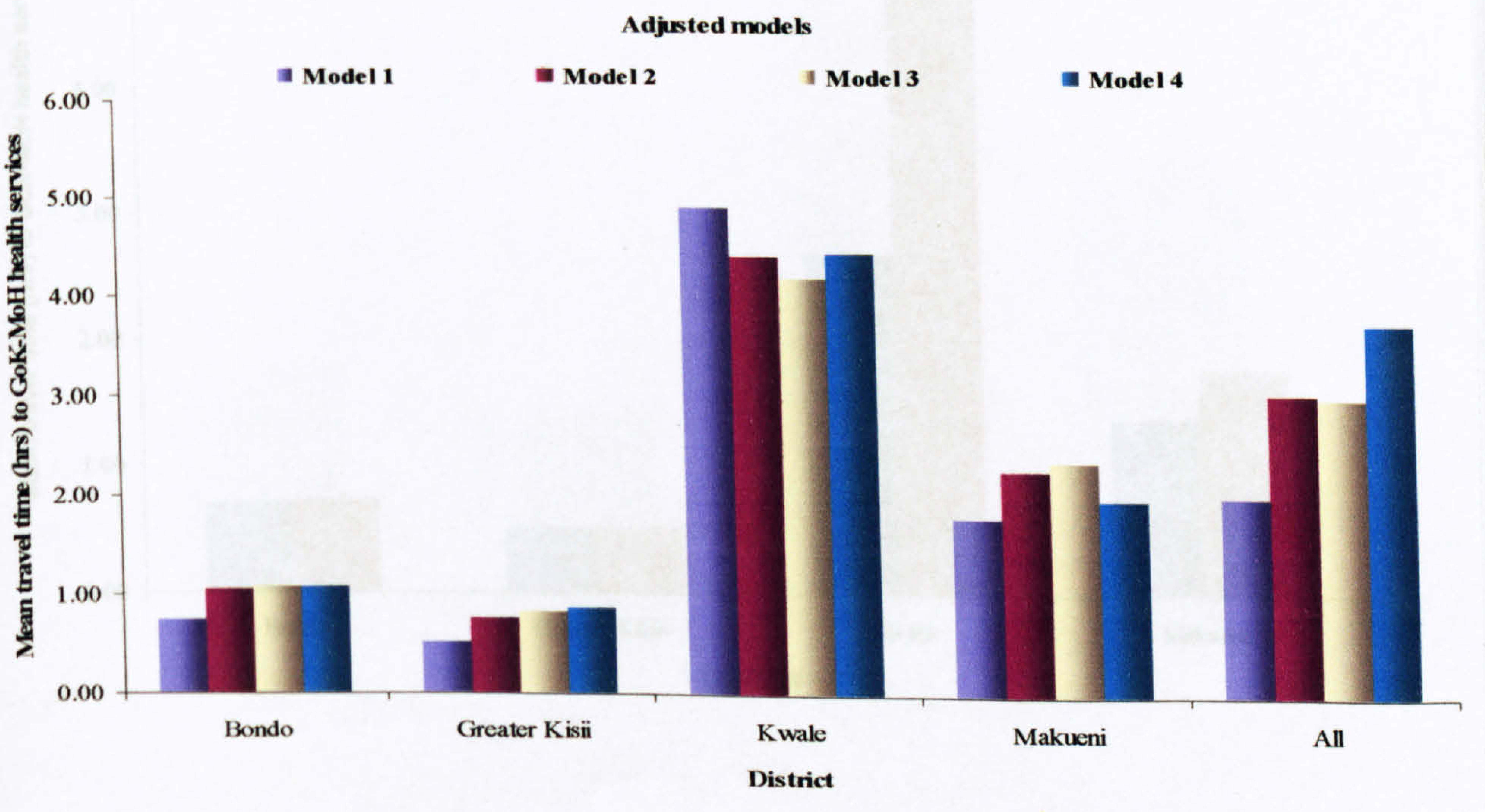


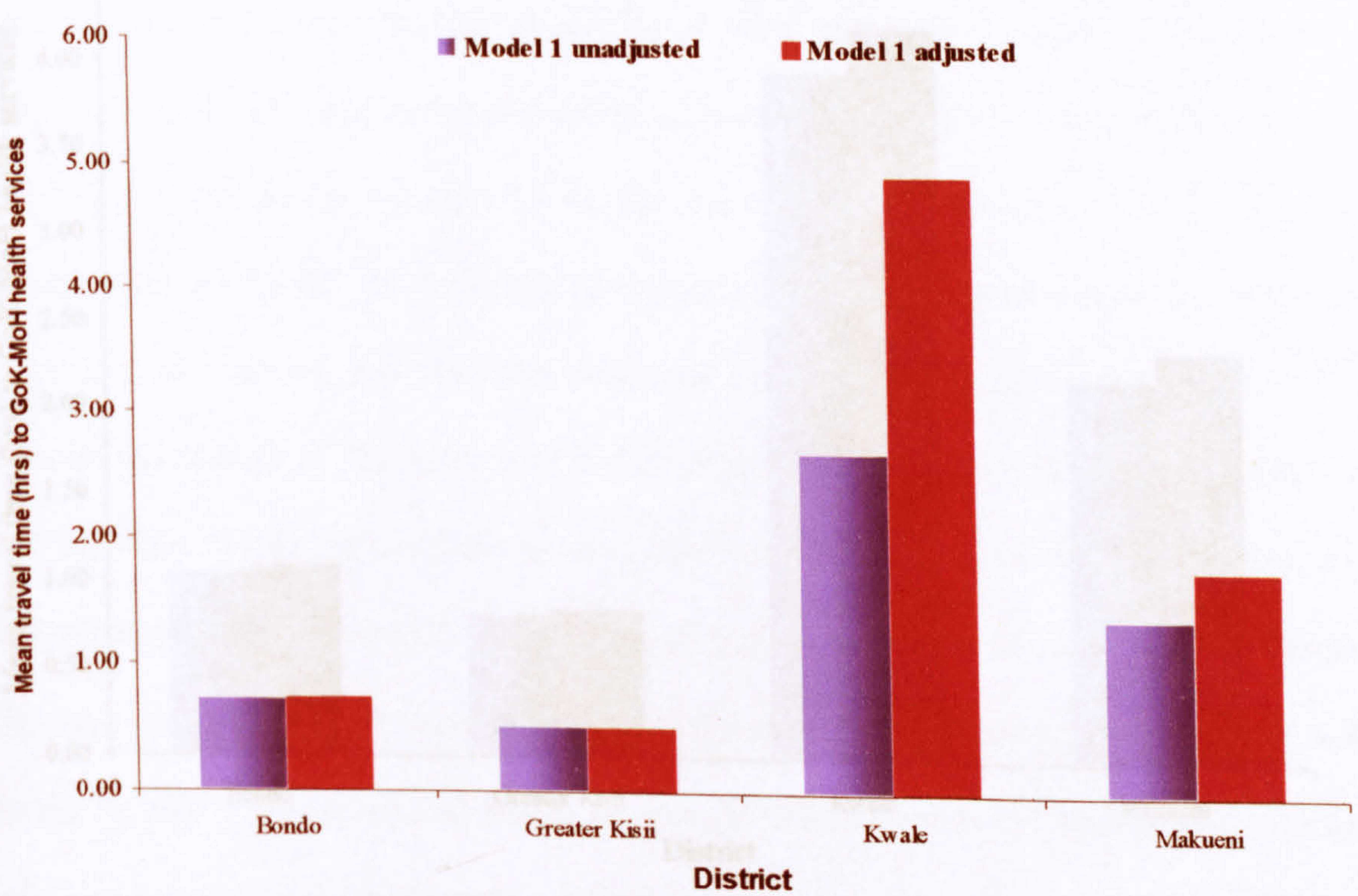
Figure 4.9 A graph comparing within district differences in the mean travel time to GoK-MoH health services between the four adjusted models in each of the study districts



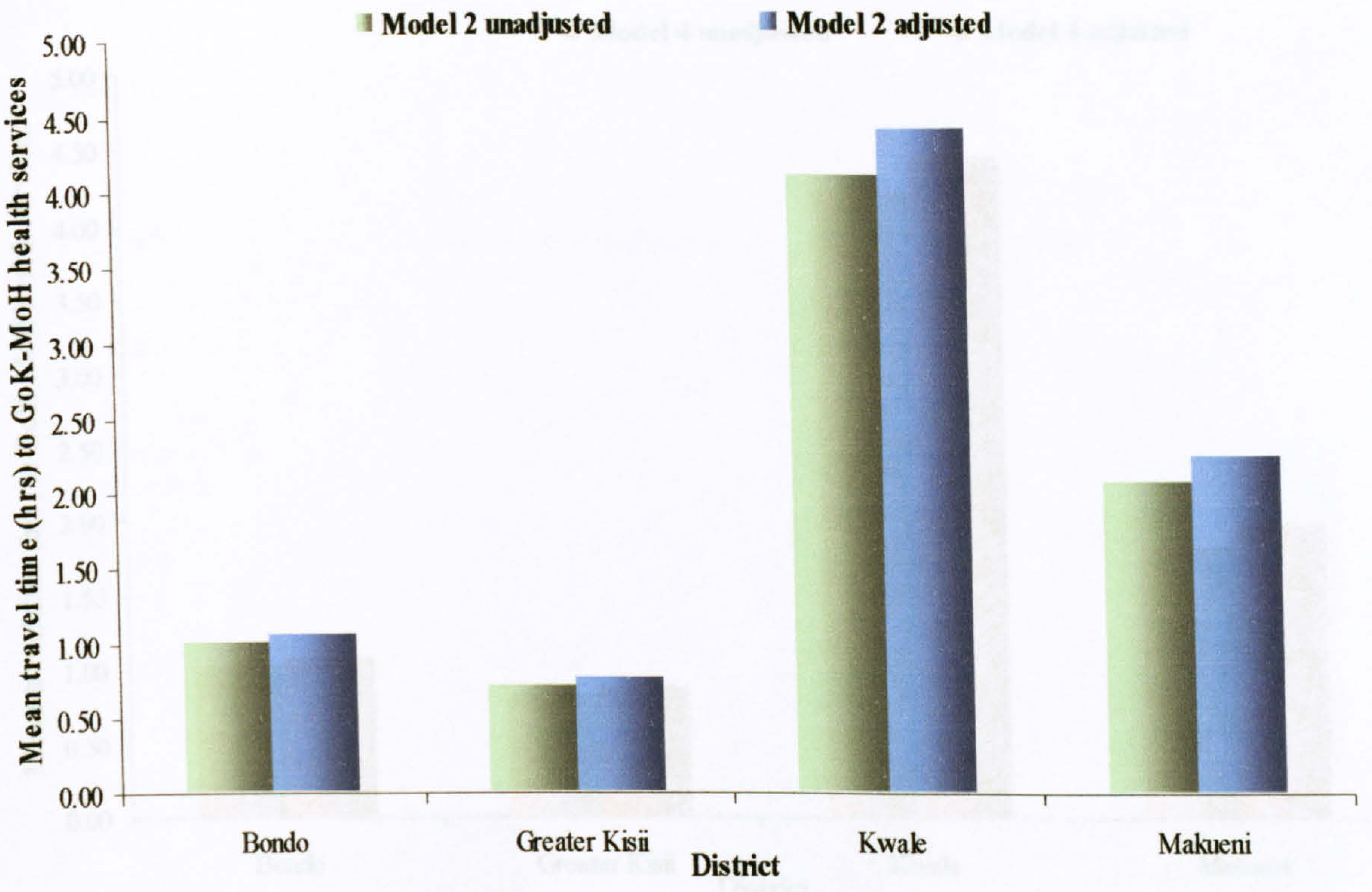
To explore the effect of adjustment of the theoretical models in the definition of access to GoK-MoH health services, a comparison of the model post- and pre-adjustment, in terms of the overall mean travel time to GoK-MoH health services, was performed as shown in Figures 4.10 a-d. The adjustment of the models increased the overall mean travel time attributed to the district, although this was greatest in Model 1 (Euclidean) for Kwale and Makueni with an increase in the overall mean travel time of 0.4-2.2 hours. In Bondo and Greater Kisii, adjustment of the Models showed a small effect compared to the unadjusted models with an increase in mean travel time of 0.02-0.05 hours across all models. Overall, the adjustment of the transport network-based models resulted in an increase in mean travel time of 0.05-0.30 hours, with the greatest change in Kwale and Makueni.

Figures 4.10 a-d Graphs comparing the mean travel time to the nearest GoK-MoH health services within each district, separately for each model before and after adjustment

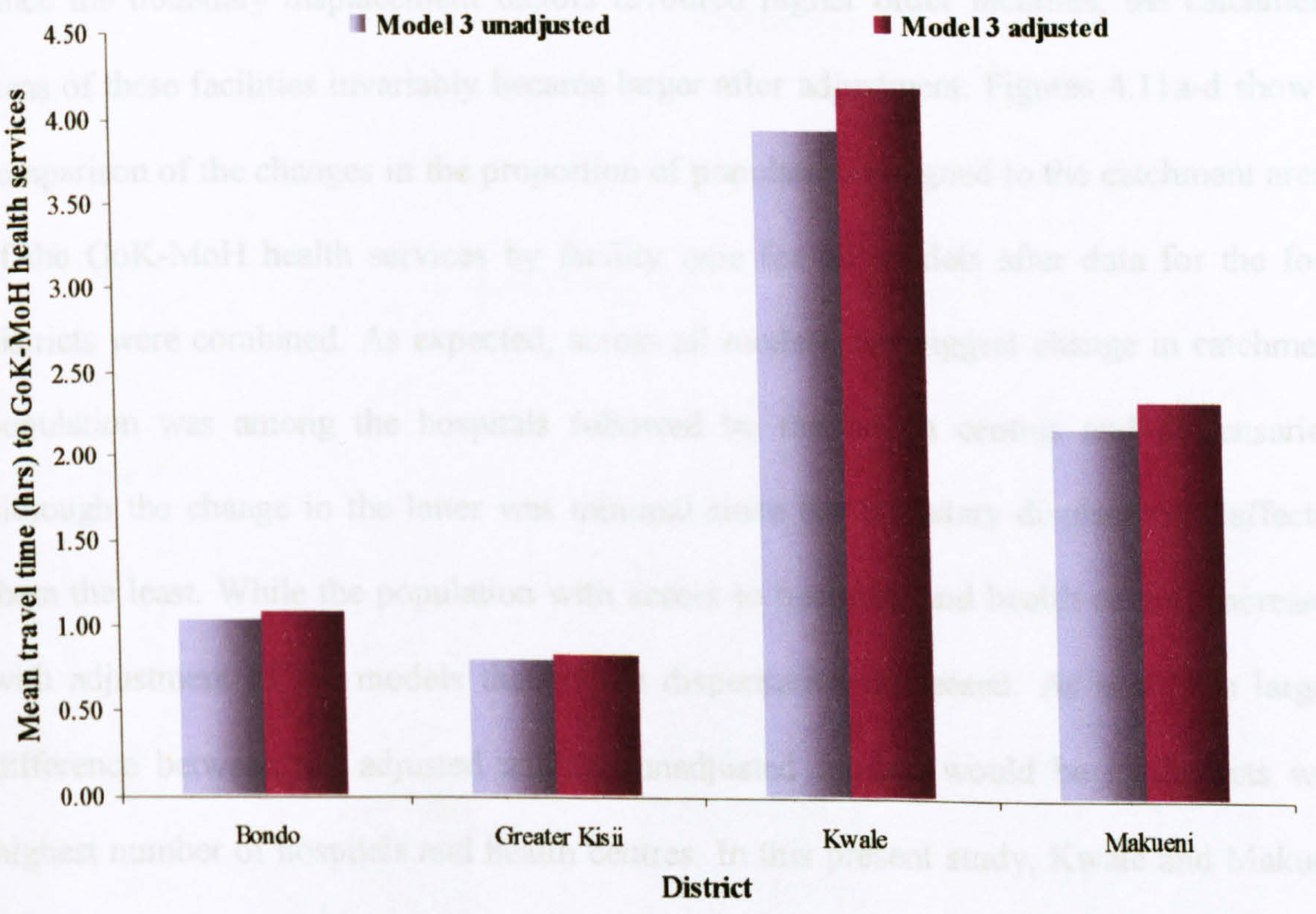
a) Model 1



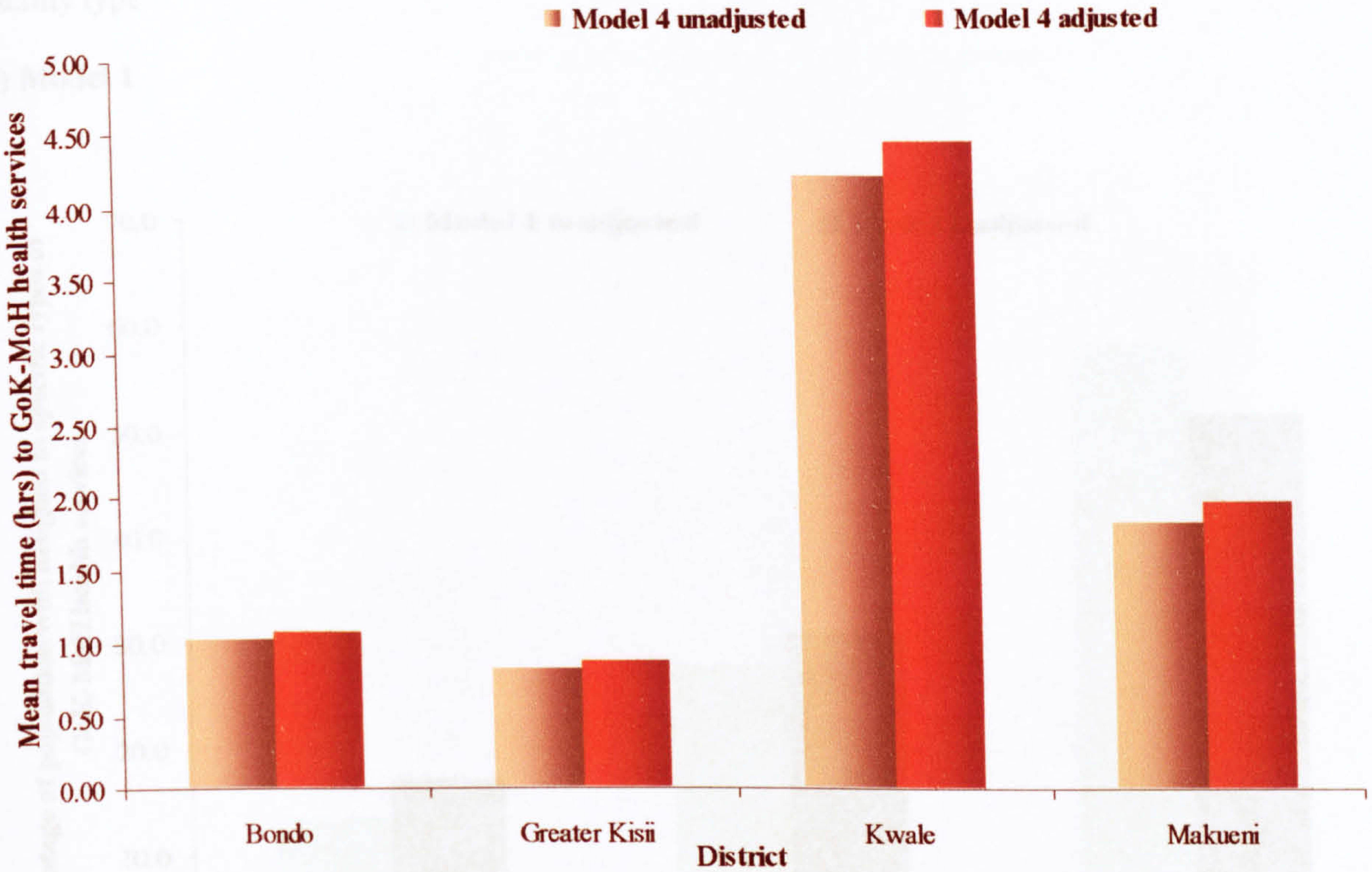
b) Model 2



c) Model 3



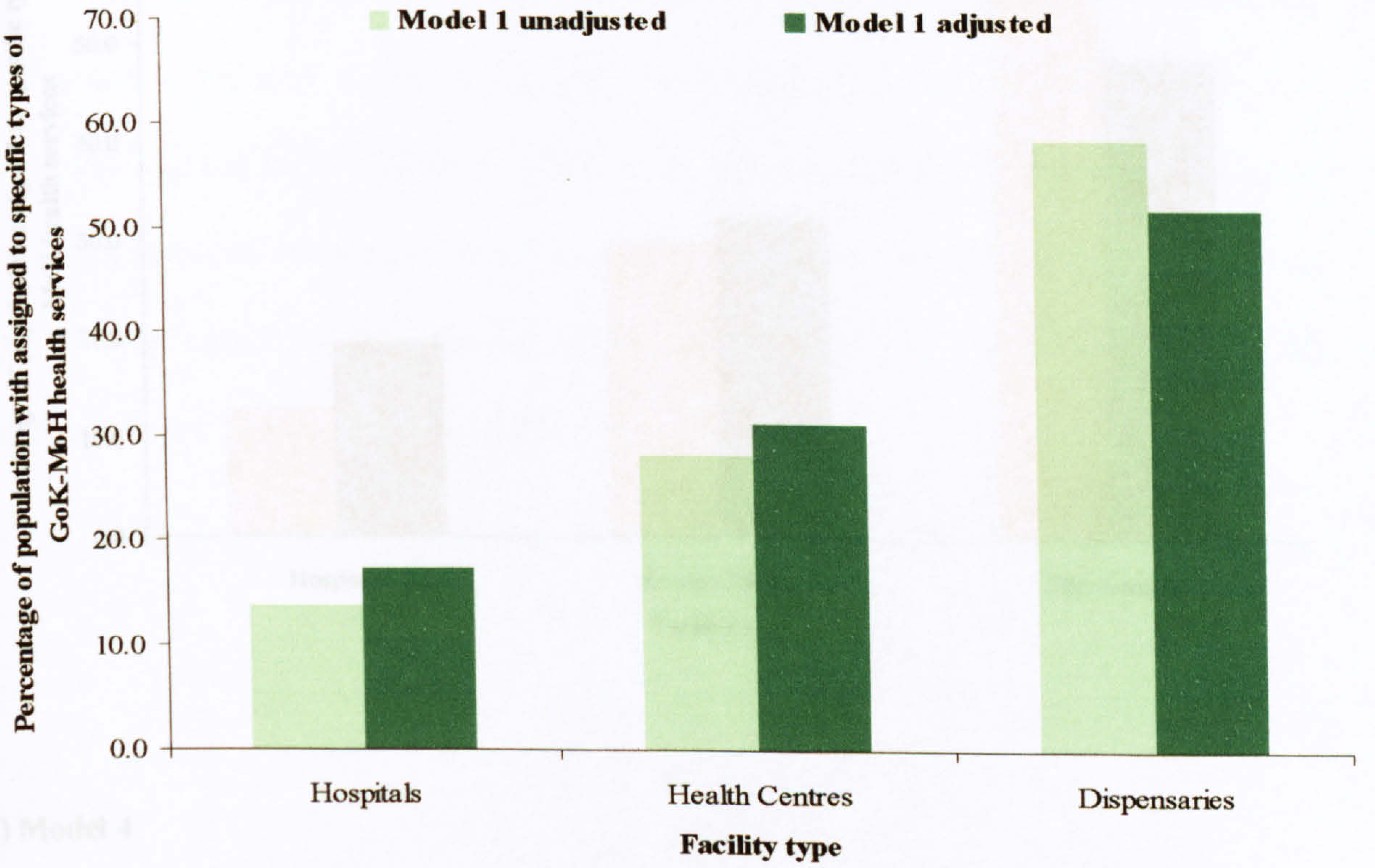
d) Model 4



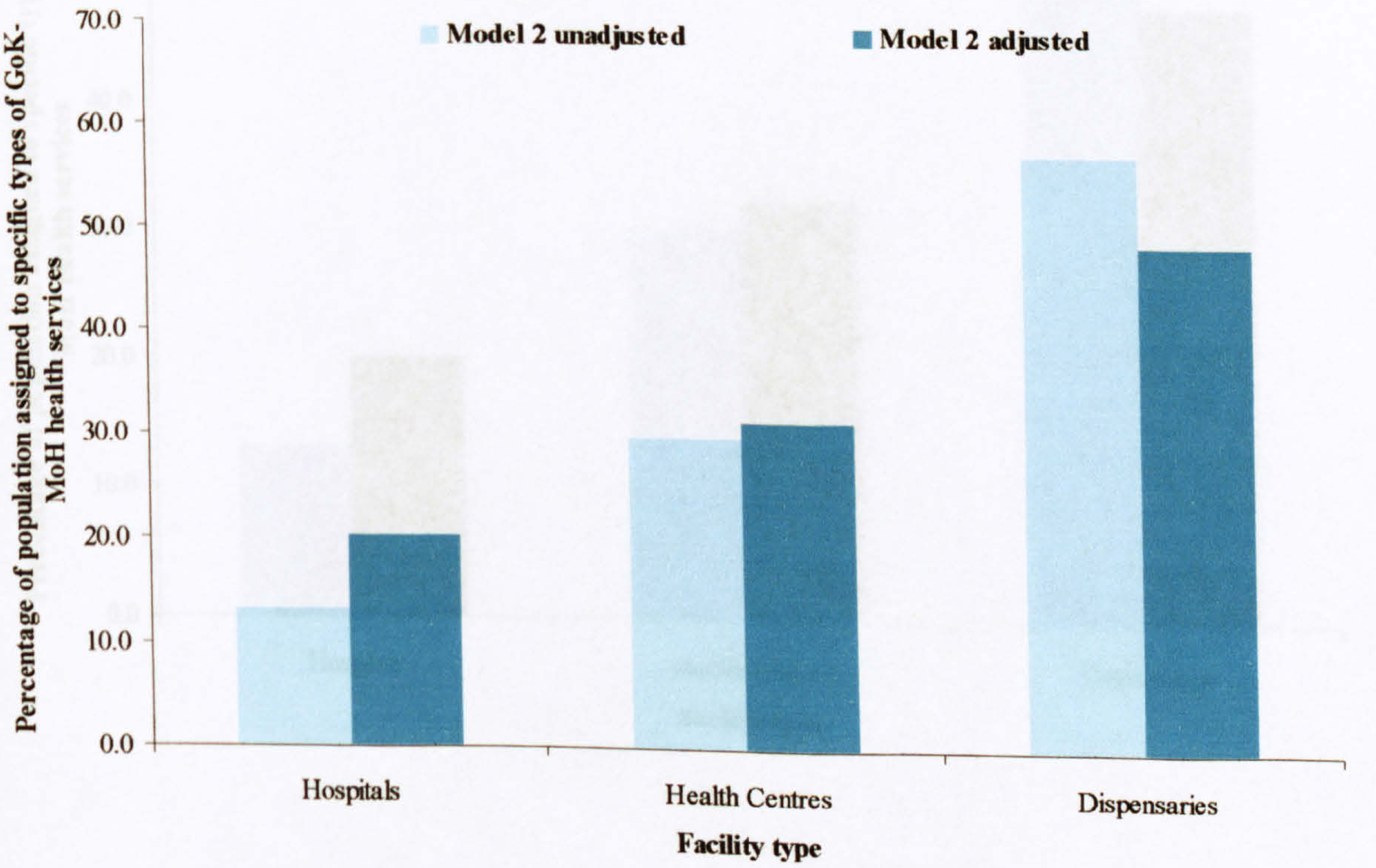
Since the boundary displacement factors favoured higher order facilities, the catchment areas of these facilities invariably became larger after adjustment. Figures 4.11a-d show a comparison of the changes in the proportion of population assigned to the catchment areas of the GoK-MoH health services by facility type for all models after data for the four districts were combined. As expected, across all models, the biggest change in catchment population was among the hospitals followed by the health centres and dispensaries, although the change in the latter was minimal since the boundary displacement affected them the least. While the population with access to hospitals and health centres increased with adjustment of the models that of the dispensaries decreased. As such, the largest difference between the adjusted and the unadjusted models would be in districts with highest number of hospitals and health centres. In this present study, Kwale and Makueni had more hospitals and health centres (Section 2.6) and as shown earlier in Figures 4.10 a-d, the difference between adjusted and the unadjusted models was highest in these two districts.

Figure 4.11a-d Graphs representing combined data for the four districts comparing the differences in the proportion of population assigned to the nearest GoK-MoH health facility for each model by facility type

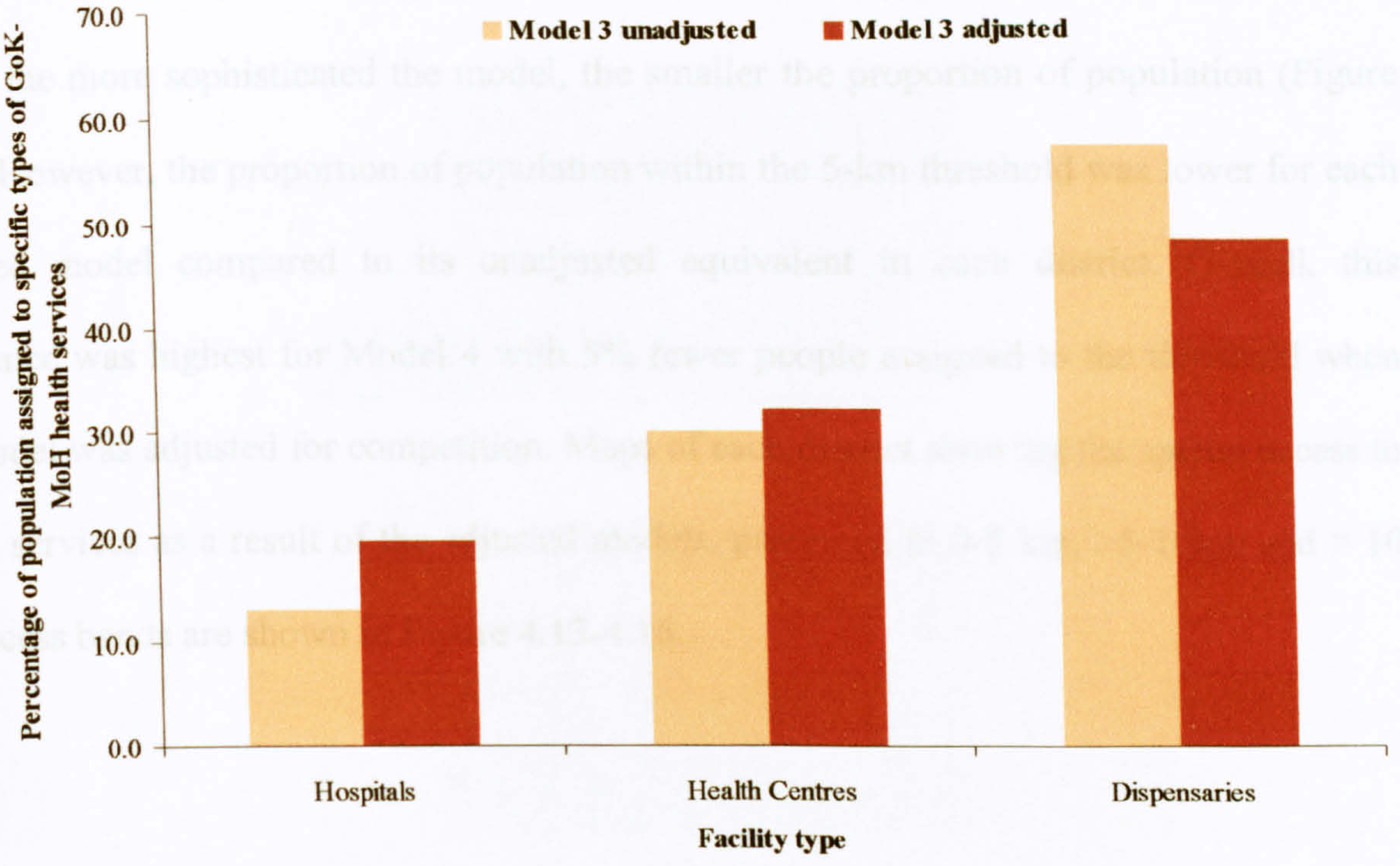
a) Model 1



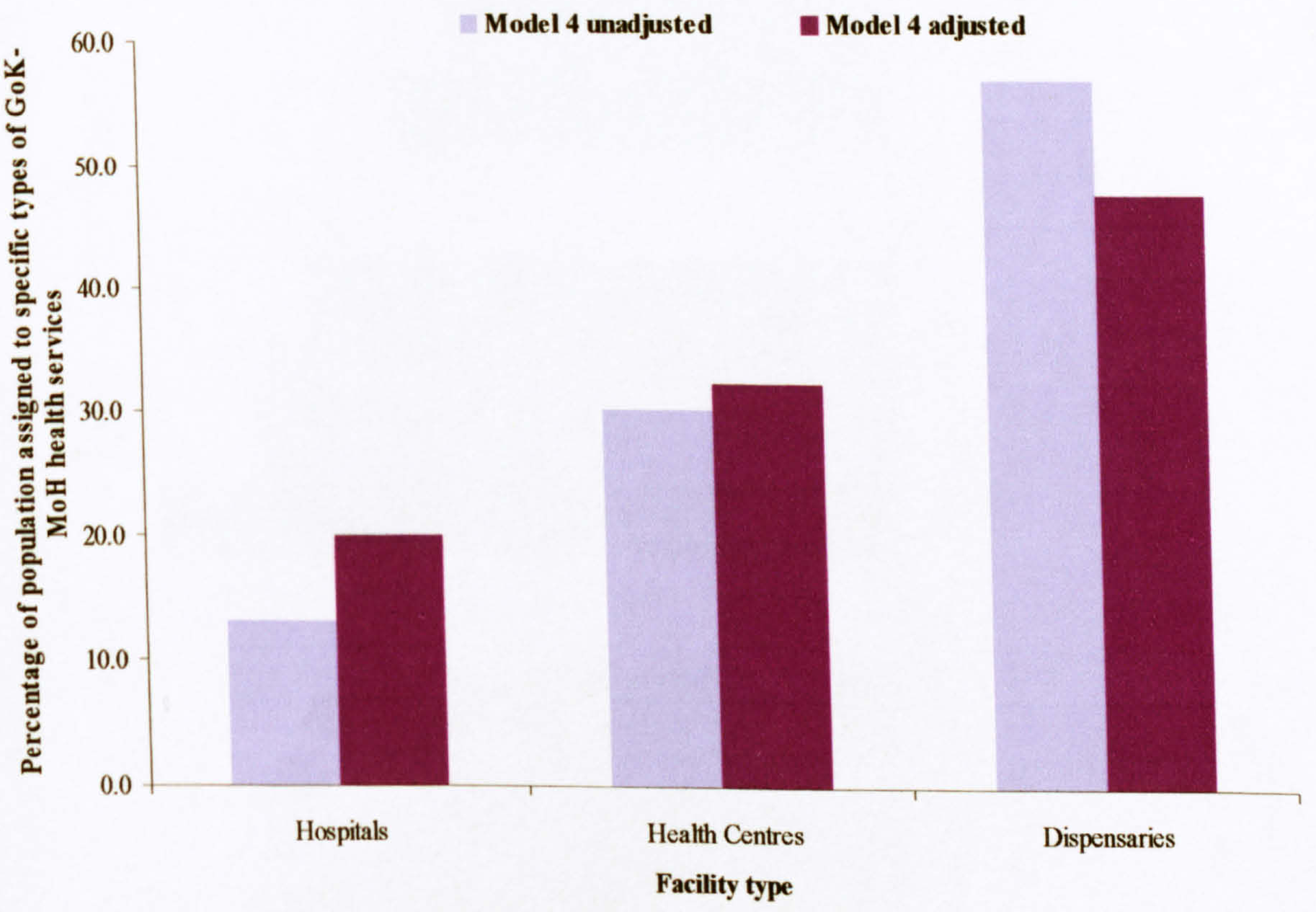
b) Model 2



c) Model 3



d) Model 4



The proportion of population assigned by each adjusted model to within 5 km of GoK-MoH health services followed patterns similar to the unadjusted models (Section 4.2.3), that is the more sophisticated the model, the smaller the proportion of population (Figure 4.12). However, the proportion of population within the 5-km threshold was lower for each adjusted model compared to its unadjusted equivalent in each district. Overall, this difference was highest for Model 4 with 5% fewer people assigned to the threshold when the model was adjusted for competition. Maps of each district showing the spatial access to health services as a result of the adjusted models, presented in 0-5 km, >5-10km and > 10 km access bands are shown in Figure 4.13-4.16.

Figure 4.12 A graph showing the percentage of population within 1 hr (~5 km) to the nearest GoK-MoH health facilities resulting from each model adjusted for competition between health facilities of different types in the study districts

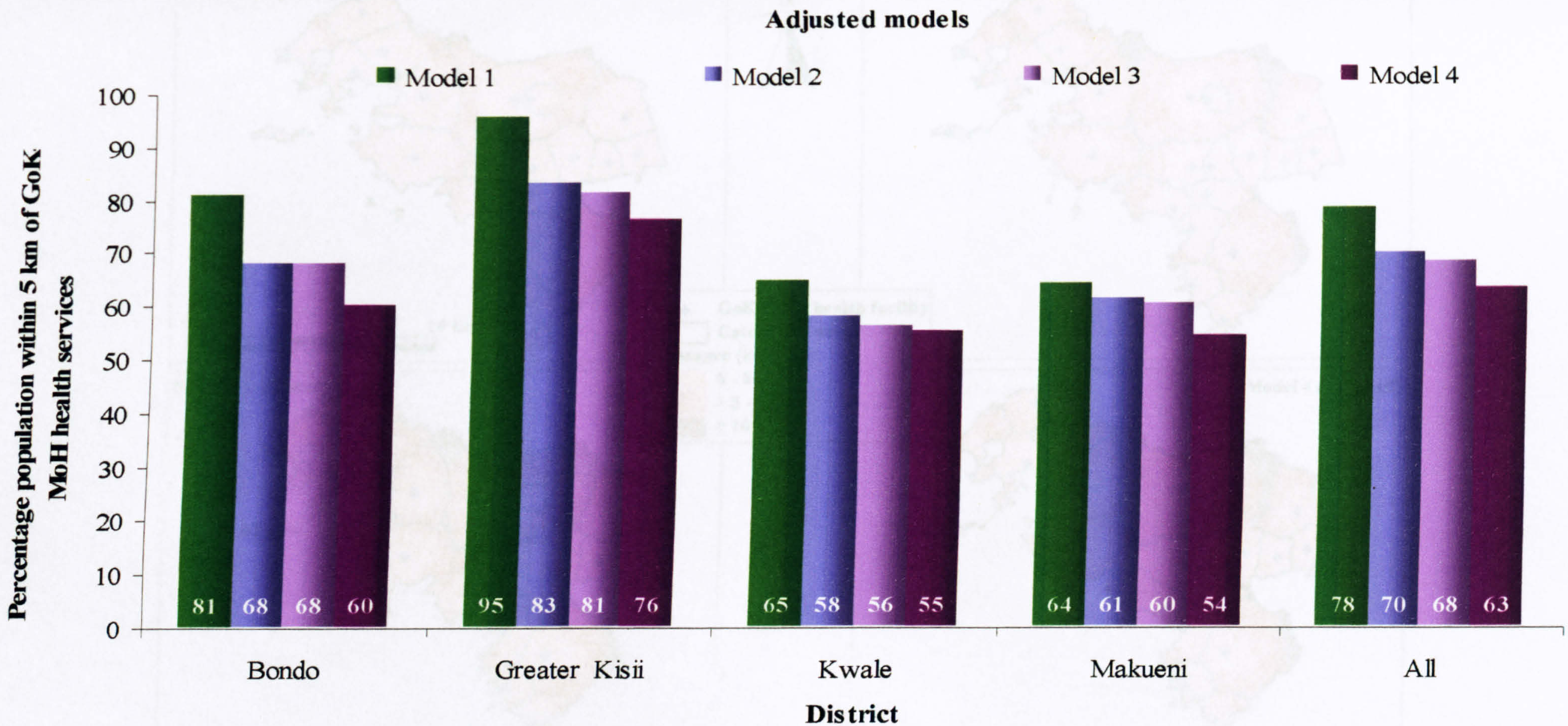


Figure 4.13 Maps of Bondo district showing access to GoK-MoH health services as a result of the four adjusted models

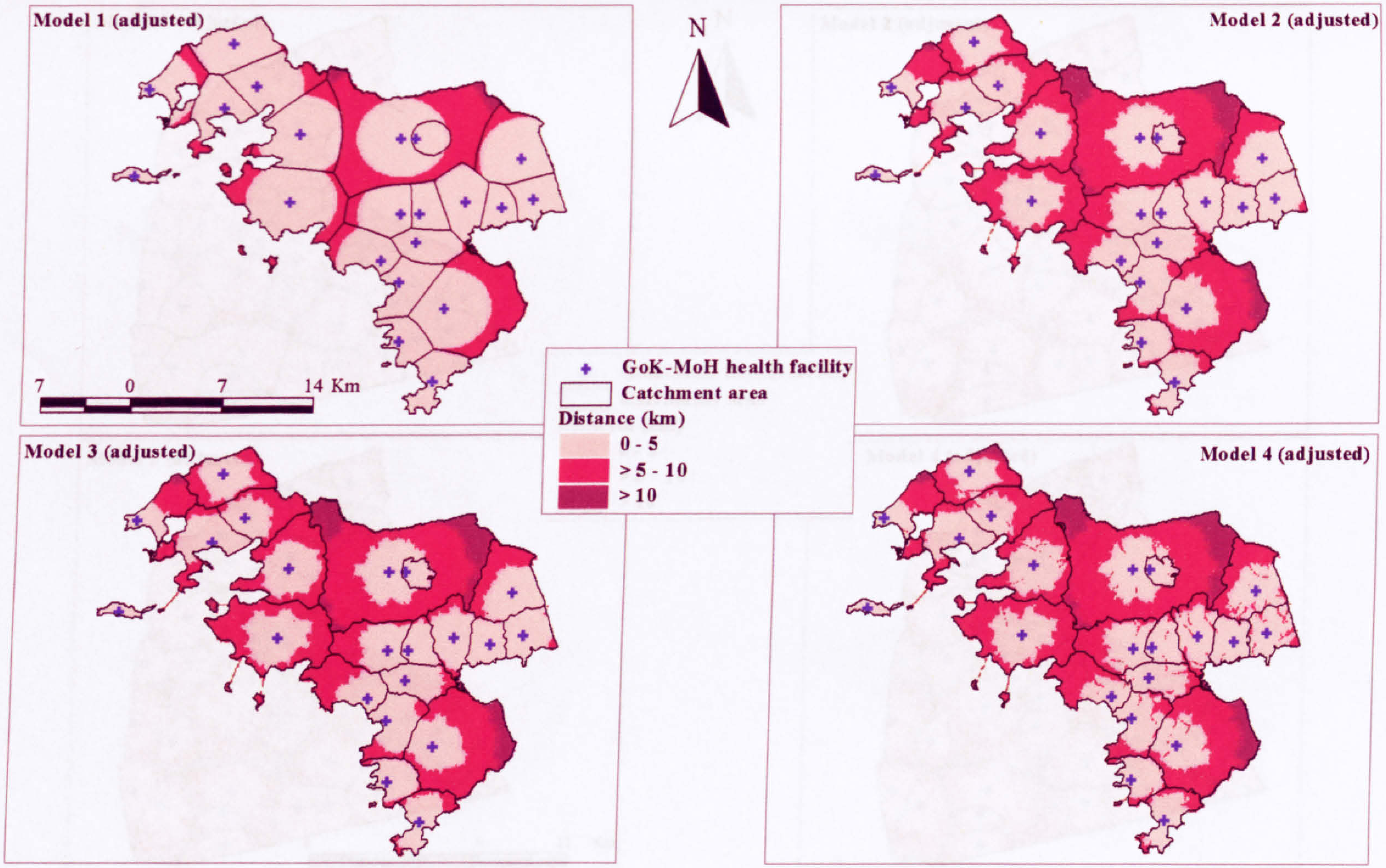


Figure 4.14 Maps of Greater Kisii district showing access to GoK-MoH health services as a result of the four adjusted models

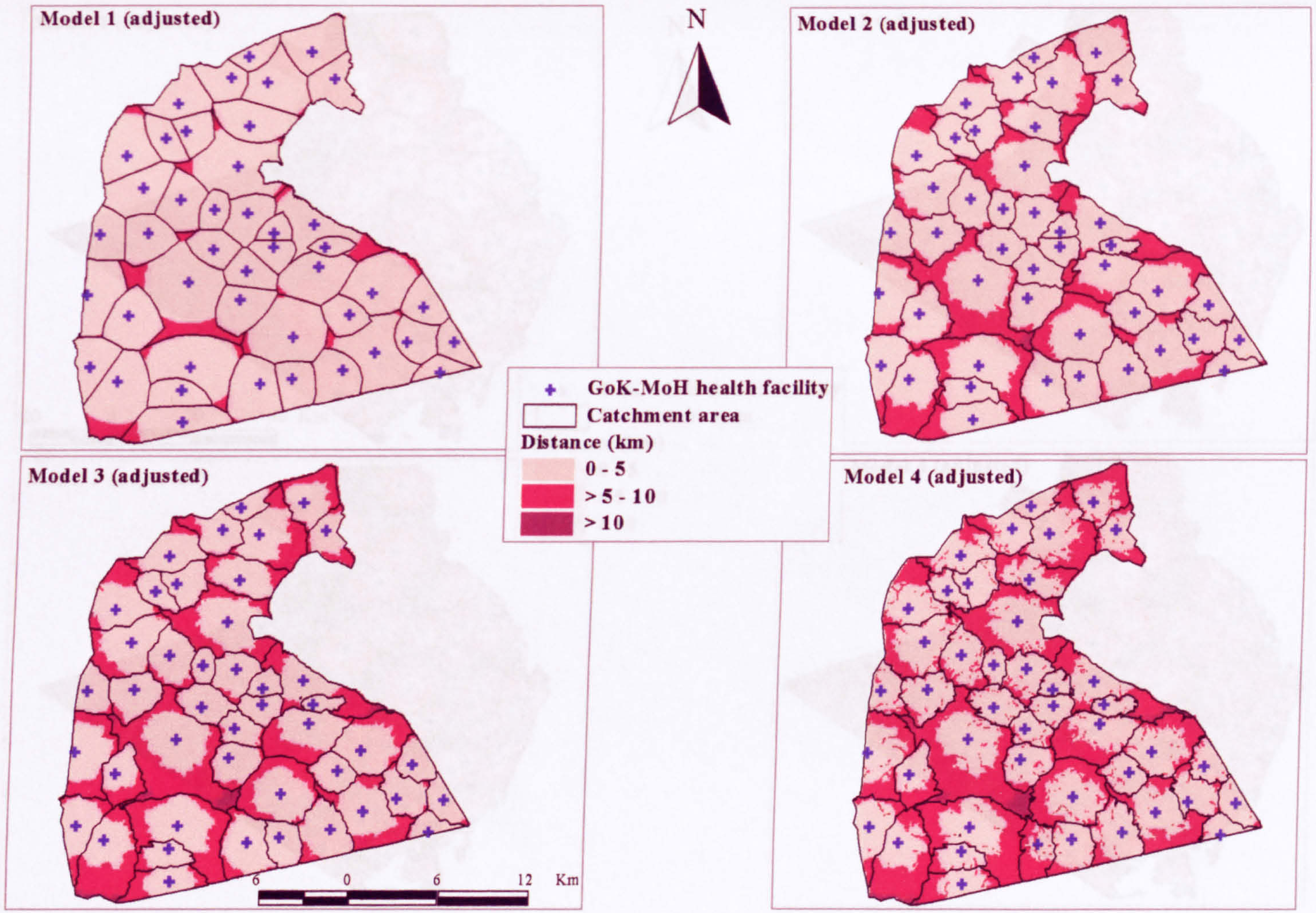


Figure 4.15 Maps of Kwale district showing access to GoK-MoH health services as a result of the four adjusted models

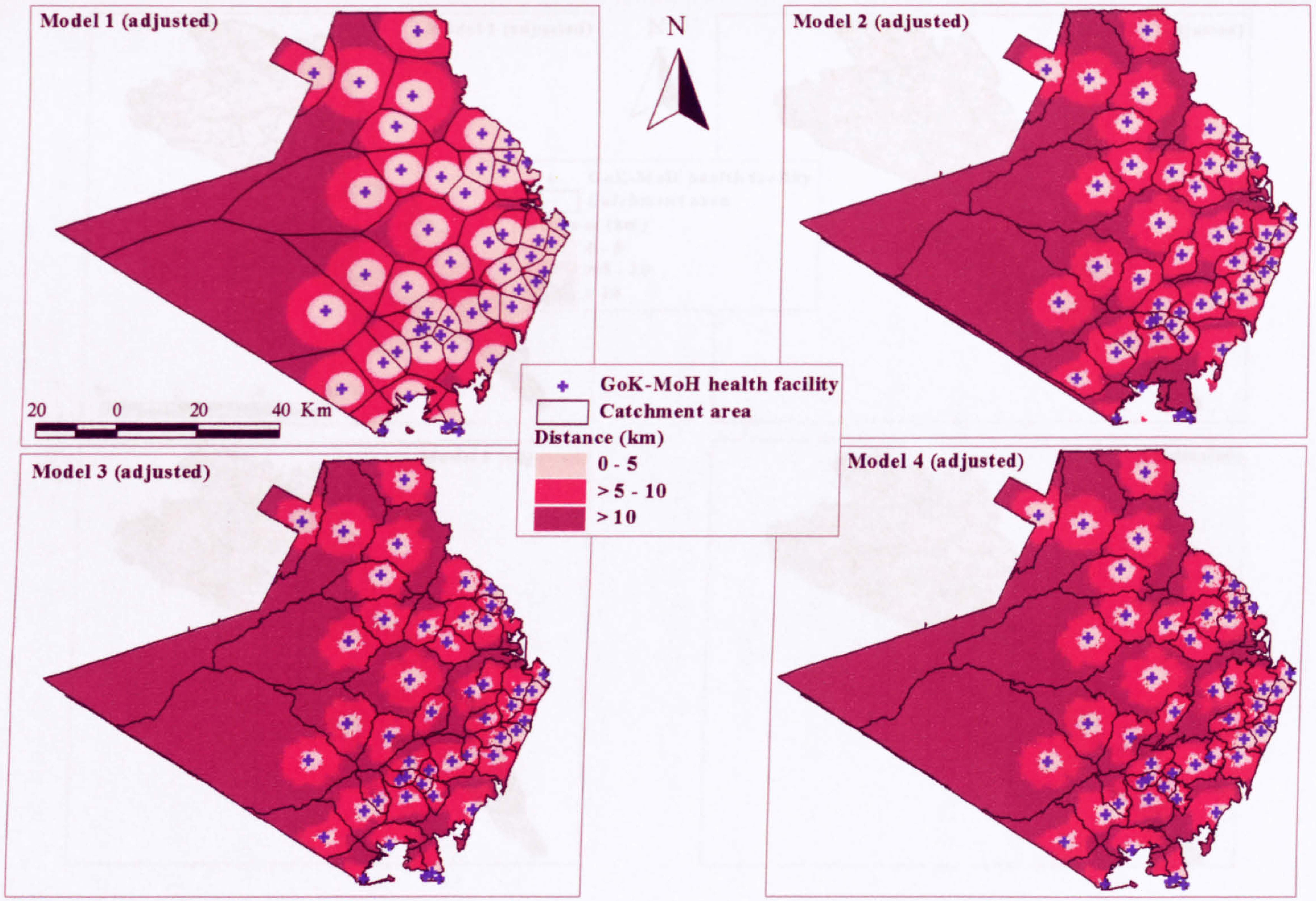
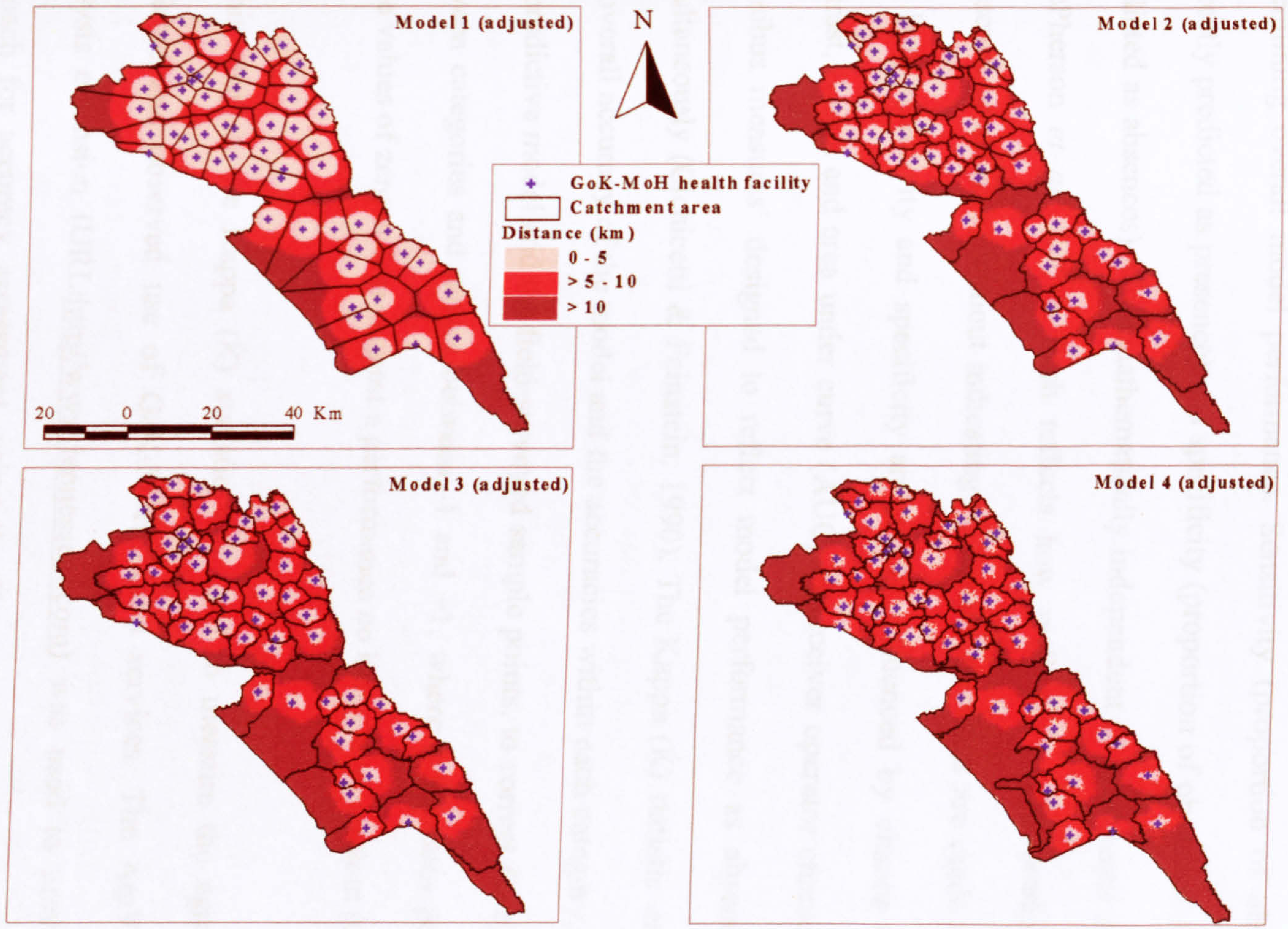


Figure 4.16 Maps of Makueni district showing access to GoK-MoH health services as a result of the four adjusted models



4.6 Model accuracy assessment

Appropriate applications of spatially explicit models are impossible without informed approaches to model development and accuracy assessment of resultant data products. Accuracy assessment provides a means of gauging model performance and provides end users with information regarding reliability and suitability of the modelling process (Fielding, *et al.*, 1997). There are several accuracy metrics available which are useful in determining overall model performance. Sensitivity (proportion of observed presences correctly predicted as presence) and specificity (proportion of observed absences correctly predicted as absences) while mathematically independent of prevalence can be misleading (McPherson *et al.,* 2004). Each reflects how well the model predicts one category (presence or absence) without indicating how many mistakes are made in the other such that both sensitivity and specificity are highly influenced by chance occurrences. In contrast, Kappa and area under curve (AUC) of receiver operator characteristic plots are 'omnibus measures' designed to reflect model performance as absence and presence simultaneously (Cichicetti & Feinstein, 1990). The Kappa (Ḱ) statistic makes use of both the overall accuracy of the model and the accuracies within each category, both in terms of the predictive model and the field-surveyed sample points, to correct for chance agreement between categories and ranges between -1 and +1, where 1 indicates perfect agreement while values of zero or less suggest a performance no better than random (Cohen, 1960).

In this chapter, the Kappa (Ḱ) statistic was used to measure the agreement between predicted and observed use of GoK-MoH health services. The ArcView 3.2 Kappa Analysis extension (URL:http//www.jennessent.com) was used to provide a packaged approach for accuracy assessment, using the Ḱ statistic as well as several additional metrics, to gauge model performance. Additional metrics include overall accuracy, overall misclassification rate, model specificity and sensitivity. These metrics quantitatively compared the models and identified the "better" model within a multi-criteria model selection process. All the accuracy metrics used are defined below:

1. Overall Accuracy: This is simply the number of correctly classified sample points divided by the total number of sample points.

2. Overall Misclassification Rate: The number of incorrectly classified sample points divided by the total number of sample points. This is the complement to overall accuracy, and may be represented as: Overall Misclassification Rate = 1 – Overall Accuracy

3. Overall Specificity: The general ability of the model to avoid misclassifying sample points as X if they are not X.

4. Kappa Statistic (Ḱ): is the chance-corrected measure of model accuracy, based on the actual agreement between predicted and observed values and the chance agreement between the row and column totals for each classification (Congalton & Green, 1999). P-values reflect the probability that a model performs better than random chance at predicting the choice of a health facility.

However, the Kappa statistic has some well-documented limitations as a test of accuracy and reliability (Byrt *et al.,* 1993; Cicchetti & Feinstein, 1990; McPherson *et al.,* 2004). While Kappa is a good measure of agreement it does not make distinctions among various types and sources of disagreement. In some cases Kappa might be low even when there are high levels of agreement (Uebersax, 1987). It is also susceptible to prevalence or distribution of observations and bias (Sim & Wright, 2005). As such it is acknowledged that Kappa is not viewed unequivocally as the default way to quantify agreement and alternatives methods such as AUC or Kappa adjusted for prevalence and bias, be explored. Despite these limitations, Kappa was used as the measure of model accuracy in thesis, largely because of the lack of data on observed travel times to health services and because it was the preferred method within the TALA group with which I worked. Models accuracies were assessed based on a Kappa accuracy criteria of <0.40= poor, 0.40-0.75=good and > 0.75=excellent (Landis & Koch, 1977). Based on these criteria, the best-fit model was selected. This model was then considered to be the definitive GoK-MoH access and utilisation model for paediatric fevers.

4.6.1 Assessment of model accuracy and selection of 'best-fit' model

The accuracy analyses of the models before and after adjustment are presented in Table 4.4. The analyses revealed that the overall accuracy (OA) of the theoretical models ranged from 0.72 to 0.74, with no difference in the OA for Model 2 and 3. The Ḱ statistic ranged from 0.71-073, again with no difference in Kappa for Model 2 and 3, implying that the predictive accuracies of the unadjusted models based on the patients using GoK-MoH health services were generally good. However, there was an almost 10-point increase in the predictive accuracies of the models when they were adjusted with OA of 0.82-0.83 and κ of 0.81-0.83. Confidence intervals for Ḱ, which are indicators of sampling errors, were wider for the adjusted models compared to the unadjusted models. However, there were no significant differences in accuracies between the adjusted models (Table 4.4).

Model 4 (adjusted) was selected as the 'best-fit' model as it had a marginally higher accuracy compared to the other models as it also had less misclassification rate. Clearly, the differences in Kappa values between the models are small and this puts in question the validity of selecting the least parsimonious model as the best-fit model. One reason for this is the nature of the data used in the accuracy analysis. The accuracy test was on whether the models assigned observed patients to the right facility they used against that predicted by the model based on the catchment area to which they belonged. On this account, apart from areas where there were significant natural barriers as shown for the facility in Figure 4.2, the catchment boundaries between facilities was affected more by adjustment for type than the definition of distance used. Although overall, the facility catchment areas did not change much, the travel time assigned to points within these catchments changed significantly from one model to the next. As such the key difference between the models was really not how the catchment boundaries changed but how travel time within this catchments changed. Therefore, the appropriate test of model reliability and accuracy would have been one that used observed travel time against that predicted by the models. However, this kind of data was available for this thesis. In the absence of appropriate model validation data, its marginally higher accuracy and the fact that both the model adjustments and travel speed definitions are based on assumptions derived from empirical data the Model 4(adjusted) was selected as the 'best-fit' model. Nonetheless, the need for better method and data for accuracy assessment is acknowledged.

Table 4.4 Predictive accuracy metrics for the adjusted and unadjusted models of access and utilisation of GoK-MoH health services for the treatment of paediatric fevers

	Overall Accuracy	**Overall Specificity**	**Misclassification Rate**	**Kappa κ**	**P-value**	**95% Confidence Interval**
Model 1 Unadjusted	0.72	0.99	0.28	0.71	0.00	0.70, 0.72
Model1 Adjusted	0.82	0.99	0.18	0.81	0.00	0.76, 0.85
Model 2 Unadjusted	0.73	0.99	0.27	0.72	0.00	0.72, 0.74
Model 2 Adjusted	0.83	0.99	0.17	0.81	0.00	0.77, 0.85
Model 3 Unadjusted	0.73	0.99	0.27	0.72	0.00	0.72, 0.74
Model 3 Adjusted	0.83	0.99	0.17	0.81	0.00	0.77, 0.85
Model 4 Unadjusted	0.74	0.99	0.26	0.73	0.00	0.73, 0.74
Model 4 Adjusted	0.84	0.99	0.16	0.83	0.00	0.79, 0.87

4.7 Computation of utilisation rate (UR) of health services

Where the aim is to understand the pattern of access and utilisation of any particular type of service or sector, information on what influences the initial decision to seek care and the subsequent choice of service provider in respect of other competing service providers is crucial. While it is sensible to consider the population in a health facility's catchment area as the predicted/potential users of that facility, this cannot be used as an estimate of the proportion of patients who actually use that facility. This requires information of the rate of use of that facility, which is derived from the proportion of patients at specified intervals within a facility's catchment area out of all patients at that interval.

The aim of this section is to model the utilisation rate of government health services for fever treatment against all other sources. Using S-PLUS script functionality, a code whose purpose was to assess the relationship between UR of GoK-MoH facilities at specific time intervals, based on the best-fit model was developed. The code required input from a single table, which contained all fever cases and for each case a column listing the journey-time to the nearest dispensary, health centre or hospital, a numeric code representing the patients' choice (i.e. 1 for GoK-MoH health facility and 2 for others). The script calculated a smoothed UR proportion at each journey-time interval. First, the UR was calculated for each journey-time interval (at intervals of 1 minute) as simply the ratio of patients using GoK-MoH facilities to all patients. These values were then smoothed by taking a moving average for each interval along the x-axis. The size of the window of moving average began at 10 and increased step-wise by a similar value until a desired smoothness was achieved. A discontinuous exponential mathematical function was used to smooth the plot. This function took the following form;

$$UR = ae^{\left[\frac{x-c}{b}\right]} \quad \text{for } x > c \text{..........Equation 4.1a}$$

or

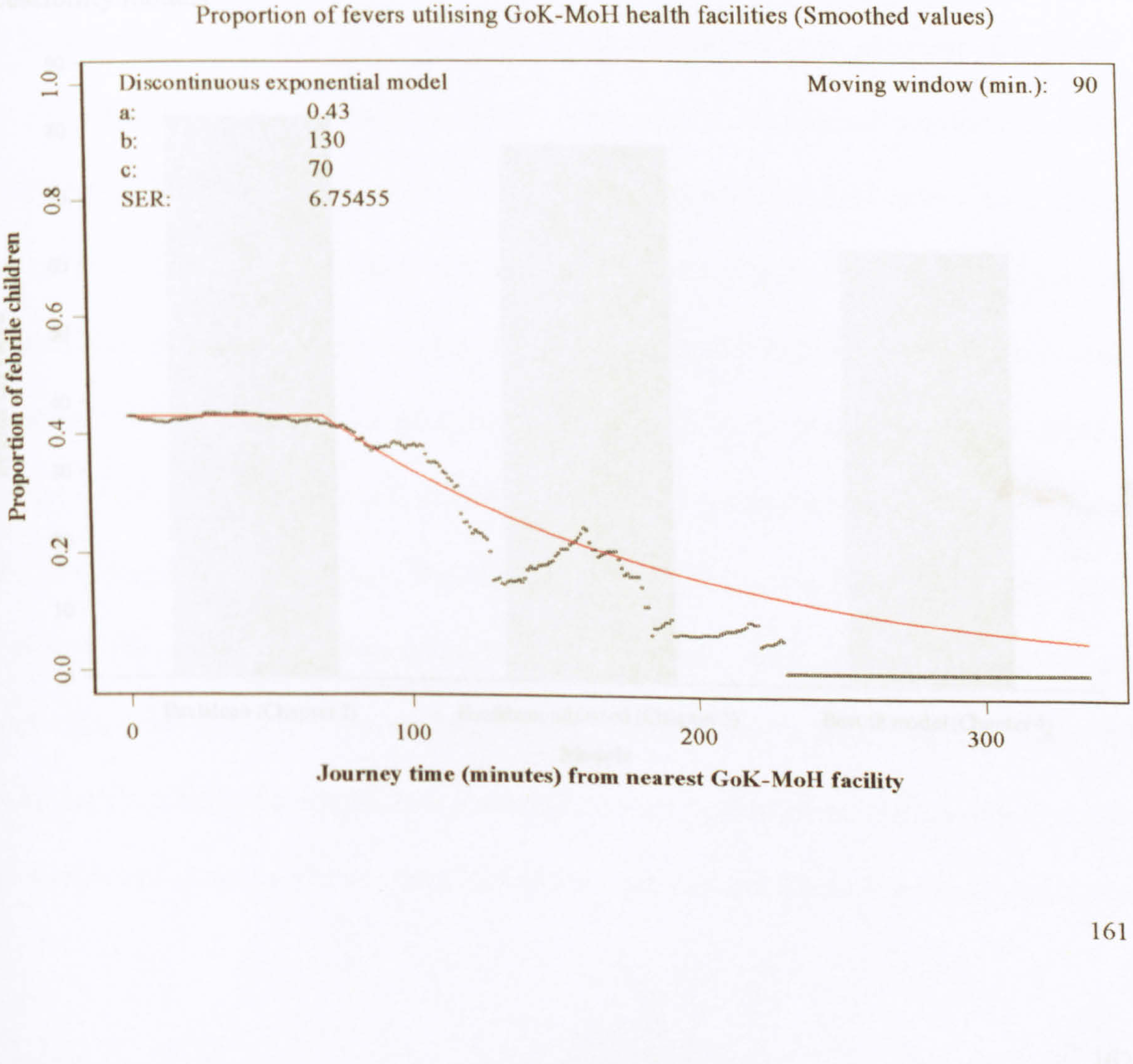
$$UR = a \quad \textit{for } x = c \text{..........Equation 4.1b}$$

Where: UR = Utilisation rate (between 1 and 0, arbitrary units); a = parameter value determining initial constant rate of UR; b = parameter value determining rate of decline of UR; c = parameter value determining distance at which UR starts to decline.

4.7.1 Overall utilisation rate of GoK-MoH health services for the treatment of paediatric fevers

Figure 4.17 shows a graph of the proportion of patients that used GoK-MoH health services at each interval smoothed using a discontinuous exponential function. The parameter C of the function represents the distance at which the utilisation rate starts to decline and represents the threshold within which most of the patients use GoK-MoH services. In the community survey this threshold was at around the 75 minutes mark, approximately equivalent to the time required to travel a distance of 6 km. The journey time was derived from adjusted Model 4, which was selected as the best-fit model after the accuracy analysis in Section 4.6. The threshold of 6-km was consistent with the result of the analysis in Chapter 3.

Figure 4.17 A graph showing the rate of utilisation of GoK-MoH health services for the treatment of paediatric fevers. The parameter 'c' represents the position of the utilisation threshold. In this case c=70 minutes, based on the best-fit model, this was approximately 6 km.

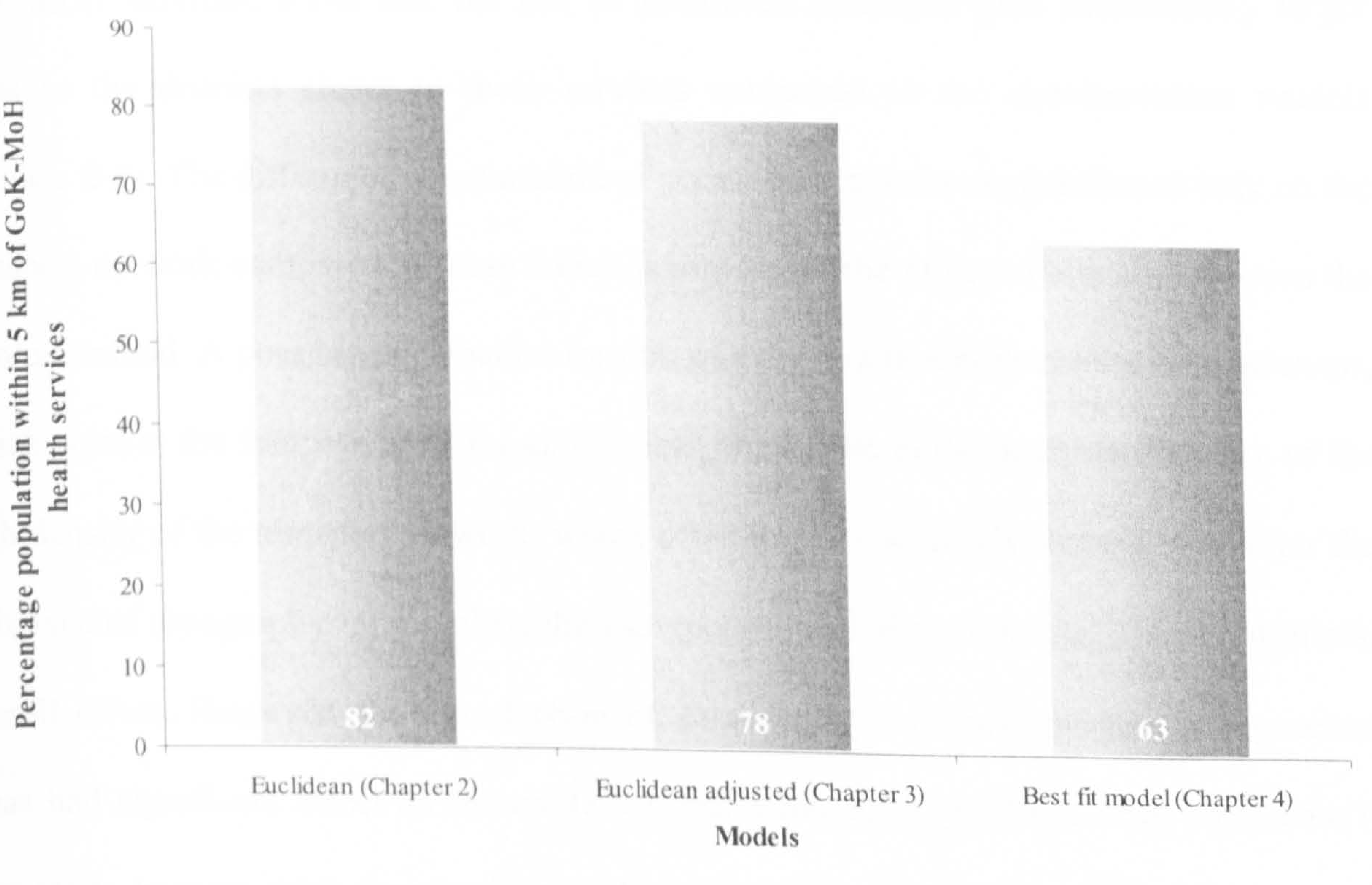


In computing the number of people who are likely to use a health facility out of all people within a health facility's catchment population, the rate of use at any distance interval is multiplied by the population at that interval.

4.8 The national implications of the different access models

In Chapter 2 the Euclidean spatial access model was explored and this was further adjusted for competition of health facilities in Chapter 3. In this chapter, a comparison of the outcome of the two Euclidean models and the best-fit model (Model 4 adjusted) developed here was conducted. The results show that best-fit model assigned 63% of the overall population in the study districts to within 5 km of GoK-MoH health services. The Euclidean model developed in Chapter 3 assigned 78% and the unadjusted version in Chapter 2, 82% of population to the 5-km threshold (Figure 4.18).

Figure 4.18 Estimates of overall spatial access to government health services as result of three main accessibility models



4.9 Discussion

This chapter, through a series of model iterations, provides a spatial framework into which the findings from the analysis of the community survey on the use of GoK-MoH health services were incorporated into theoretical spatial access models. The aim of the modelling exercise was to develop spatial accessibility models for GoK-MoH services in Kenya that overcame the limitations of existing approaches while making full use of public domain data.

A limitation in most accessibility modelling approaches is the use of Euclidean or straight-line distances in measuring the time taken to travel between patients' places of residence to the nearest health services. The modelling exercise in this study overcomes this limitation by developing models that incorporate the transport network. In addition, the models also account for the effects of elevation and other natural barriers to people's movement on the transport network. These models, all of which measure the distance (travel time) to nearest GoK-MoH services, show that the use of Euclidean distances puts substantially larger areas in the districts closer to these services compared to the non-Euclidean models (Models 2-4). The difference in estimation of access between the models based only on the transport network compared to those which incorporated the effect of elevation was on the whole minimal. A possible explanation for this was the fact that high-resolution road maps, which were at the footpath level for all districts, were used in the analysis. Because of the high density of the transport network, which often mirrors society's attempt to counter the influence of topography on mobility, the incorporation of elevation data, showed minimal overall effect. However, the introduction of data on rivers, lakes, swamps and gazetted areas had significant effect on the models. Greater impact might have been noticeable if man-made barriers such farmland and settlements were included in the analysis. Areas where the effect of these barriers were concentrated showed substantial increase in time to nearest GoK-MoH health services and subsequent transformation of the facility catchment areas.

Using distance to the nearest health services as a measure of access and utilisation of health care, regardless of how sophisticated the definition of distance is, remains sub-optimal. Previous research work has shown that other factors, many of them aspatial as described in the review in Section 1.5.2, determine whether or not one uses the nearest source of health care. The TRANSECT algorithm implemented in this study explored the spatial differentials in use of any two neighbouring GoK-MoH facilities for the treatment of paediatric fevers. The analysis revealed that where the two neighbouring facilities were of the same type, patients' actual use of either facility was not as significantly different from assumption that patients' used the nearest one. However, where the pair of facilities was of different types, the higher order facility showed a larger draw and the boundary between the two facilities displaced in its favour. This approach attempts to provide a way of measuring the factors which are not necessarily driven by geography, such as the effect of varying qualities of health services on choice, but whose existence can be spatially defined. Another important aspect of this approach was that it provided a measure of overlap area where cross-border use of adjacent health facilities takes place. This was defined by the limits of the 95% CI around the position of the discrete boundary between adjacent health facilities. A limitation of the data, which restricted this approach, was that there was insufficient information to account for the unique characteristics of the individual facility and its users, restricting the definition of displacement factors by facility type only. Random effects of individual pair facilities were found to exist during the modelling exercise in which, for example, a dispensary was found to have a higher patient attraction than an adjacent health centre. There were other instances where two neighbouring dispensaries were also found to have perceptibly different patient attraction. Although these were only in very few cases and were considered not to significantly affect the general trend of utilisation, it is acknowledged any higher resolution modelling exercises ought to incorporate these individual facility-level peculiarities.

The algorithm for adjusting the theoretical models based on nearest distance to GoK-MoH health services is one that, to the best knowledge of the author, has not been applied elsewhere in health service access and utilisation modelling. Adjusting the theoretical models for actual use substantially improved their predictive accuracies. However, between the adjusted Models (1-4) there were minimal differences in predictive accuracies, although adjusted Model 4 was marginally more accurate. From the analysis presented in Chapters 3 and 4, it was clear that most patients who attend GoK-MoH health services came from within 6 km regardless of the type of model used to define distance. By extension, all models would have similar accuracies at this distance. Therefore, the true test of the accuracies of the models would be determined by how well they predicted for patients living beyond 6 km of GoK-MoH services. However, only 9% of the patients who used GoK-MoH health services in the community survey came from outside this distance. In the absence of sufficient test data, adjusted Model 4 was selected as the best-fit model, because it had marginally higher accuracy and it incorporated more distance variables than the other models. The chosen model incorporated the transport network, elevation, rivers and other waterbodies and gazetted areas and was adjusted for competition of health facilities of different types. Applying this model to define catchment areas revealed that 63% of the population in the study districts lived within 5 km of GoK-MoH health services. This was 19% less than the Euclidean model developed in Chapter 2, which represents the current estimates of access to health services. When the Euclidean model was adjusted for competition in Chapter 3, this proportion was reduced to 78%. This result, that the current estimates of spatial access to government health services assigns 19% more people to the 5-km threshold than the best-fit model, has important implications for the for the health care access goals in Kenya. If the outcome for the study districts was taken to represent the estimate of national access to government health services, about 6 million people who are thought to have access to GoK-MoH health services within 5 km will actually be outside this threshold.

The potential users of a health facility, derived from accessibility models, are measured as the size of the population within the facility's catchment area. From this population, only a certain proportion will actually end up using the health facility in any given period of time while others will seek care elsewhere. Therefore, the effect of the array of competing non-GoK health service providers needed to be accounted for to accurately estimate the likely patient load at a GoK-MoH facility. 'Gravity models', initially developed for land use planning (Hansen, 1959) have been used elsewhere in combining the potential interaction between any population points and competing health service points at a given distance (Section 1.6). The problems with the gravity models are that a single distance decay coefficient is required which is difficult to derive for health services, as such the facility attractiveness is intuitively assumed to decay at a constant rate (Guargliardo *et al.,* 2004). The method of computing utilisation rate described in this chapter models the rate of use of a GoK-MoH health facility at any given interval as the proportion of all patients using the health facility at that interval. It is easy to implement, was based on empirical data and can be used within a spatial framework.

In summary, the model developed here overcomes most of the limitations faced in existing accessibility models. Significant differences have been found between the Euclidean model and those based on the transport network. The model incorporates actual patients' use of services in defining catchment areas and does not assume that people always use the nearest health services. These novel approaches of spatially adjusting discrete boundaries are applicable not only to defining health service catchment areas, but also in other analysis that require distribution of boundaries of any adjacent spatial features. Ways of measuring cross-border use of services and variations in access and utilisation of health services within a facility's catchment area have been defined. A threshold of access and use of services based on empirical data has been computed and each population point assigned a value of access to GoK-MoH services. The best-fit model revealed that about 63% of the population had access to government health services at 5 km, 19% less than is currently estimated through the use of the Euclidean model.

In Chapter 5, the possibility of scaling-up the best-fit access and utilisation model developed here to the national level using lower resolution data of national health services and other input data will then be explored. The utility of the access model for measurement of development of goals will be discussed.

CHAPTER 5:
Developing a National GIS health service database to assess its potential for defining access to health care in Kenya

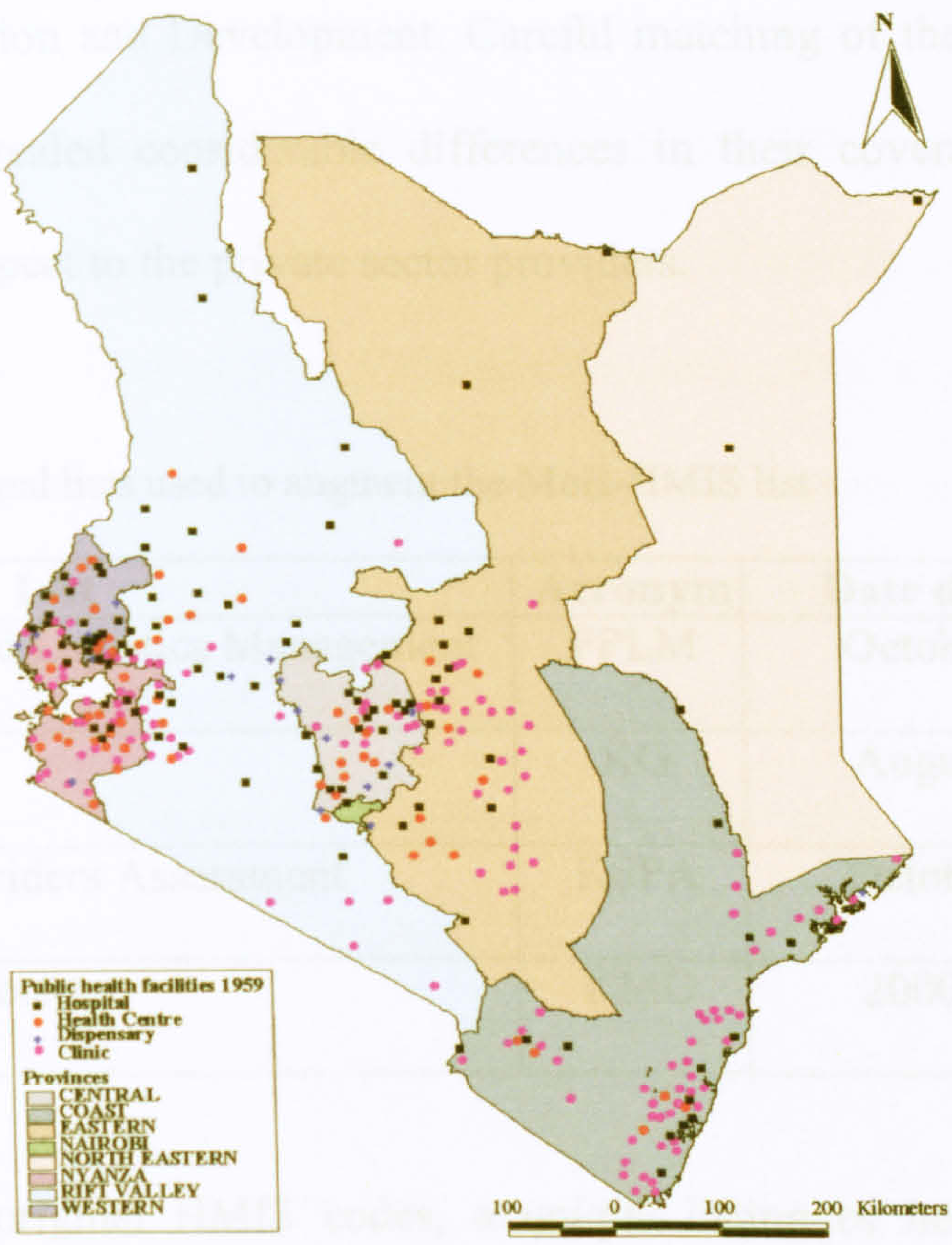
5.1 Background

The previous three chapters have examined a number of spatial features of health service access and use within four selected Kenyan districts. The analysis of variables of access to and use of services was made possible because of an investment in developing district-level, high resolution, spatial information on health services and population. In Chapter 4, a definitive access model to GoK-MoH health services was developed for the four study districts. This model was based on access to health services on the transport network adjusted for elevation, rivers and other waterbodies, parks and forests and the actual use of services by patients. The full utility of this model depends on scaling it up to the national level, which is the aim of this chapter.

Scaling-up the model developed in Chapter 4 requires comprehensive spatial data at the national-level. First, accurate and precise data on health service location and type is required, followed by information on the size and distribution of population. In addition, information on the transportation routes linking populations to health facilities and the land-cover/land-use factors that influence people's movement on these routes is required. In Kenya, the last complete map of health service providers was developed in 1959 (Butler, 1959; Figure 5.1). For over forty years there has been no concerted effort to provide a reliable map of health service providers nationwide.

This chapter describes how it is possible to construct a national database of health service providers from a diverse and disparate series of data sources. Factors affecting the accuracy and the feasibility of the spatial dimension of the health service database are then examined. In addition, a description of a national population transport network, land-use and land-cover and topographic database is given. Finally, the potential and limitations of these nationally available data in scaling-up the access and utilisation models developed in Chapter 4 to the national level to define inequities in health service access is discussed.

Figure 5.1 A 1959 Kenya map of Health facilities* (n=313) digitised from 1959 Atlas of Kenya[a]



*This 1959 Kenya digital map of health facilities was derived from a scanned Atlas of Kenya, 1959 Butler map of medical facilities (Butler, 1959). The scanned map was overlaid onto a 1999 provincial map of Kenya onto which health facility points were manually transferred. These were then digitised on-screen using Arcview GIS (Version 3.2, ESRI,Inc. New York, USA)

5.2 The National Health Service database (NHSD)

5.2.1 Developing the NHSD

The project began anticipating a single, definitive list of all service providers nationwide held centrally by the Ministry of Health (MoH). Four principal lists existed, created at different times (1998-2000) as shown in Table 5.1. These included a list held by the MoH-HMIS division (last updated in April 2001), an independent list created by the Family Planning and Logistics Management (FPLM) program supporting the supply of commodities for the Ministry of Health's Division of Reproductive Health (developed in October 1998), the Kenyan Government's Gazette (KG) notice of officially recognized health service providers posted in August 1998 and the Kenya Service Providers

Assessment (KSPA) report which was conducted in 1999 by the MoH and the National Council for Population and Development. Careful matching of these lists for names and district location revealed considerable differences in their coverage and completeness, particularly with respect to the private sector providers.

Table 5.1 Four principal lists used to augment the MoH-HMIS list

List	Acronym	Date developed
Family Planning and Logistics Management	FPLM	October, 1998
Kenya Gazette	KG	August, 1998
Kenya Service Providers Assessment	KSPA	October, 1999
Kenya Medical Directory	KMD	2000 Edition

By retaining the original HMIS codes, a unique listing of health facilities including facilities found on the other key lists, was created. These lists were then augmented through a number of different information sources and correspondence. First, the CBS of the Ministry of Planning and National Development were contacted to source District Development Plans for 57 districts, these sometimes provided hand-drawn maps and lists of facilities located in each district (52 districts). Second, additional non-GoK-MoH lists of service providers were obtained from the Christian Health Association of Kenya (CHAK) developed in September 2000 (CHAK provides umbrella support to the mission health sector in Kenya). Likewise the Kenya Medical Association provided the Kenya Medical Directory (KMD) 2000 edition, which contained a list and addresses of their national members practicing care within the public and private sectors. Telephone directories were also checked for each of the eight provinces to identify listed private practitioners. Non-Governmental Organisations (NGO) and research organisations were contacted to provide any annual reports or publications which might contain health facility lists and maps. Data on facility name, district, address and telephone numbers were listed in an excel database.

Lists of health facilities run by the Ministry of Health (MoH), Mission, NGO and Local Authorities (LA) were abstracted from the main data and used as provisional lists. Various NGO's and research groups who worked within specific districts were also approached, Provincial Health Teams were then asked to correct and supply new information in June 2002, August 2002 and January 2003. Between November 2003 and April 2004 provisional maps and lists were produced and distributed to every district (n = 70) for DHMTs to review and return with corrections and updates. At the time of writing the thesis, 54% (38/70) districts had responded. The following sections describe the methods of spatial positioning and their accuracies as compared to the GPS coordinates, which were considered as the 'gold standard' in this study, a reasonable assumption post-selective availability (Hay, 2000).

5.2.2 Developing spatial coordinates for health service providers

Global Positioning Systems (GPS) coordinates: A number of research and NGO groups have developed high-resolution maps for epidemiological studies and to support DHMT as part of decentralised health reform. These included support from the Danish International Development Agency (DANIDA) to Coast province in 2001 to develop a linked HMIS system for disease reporting (seven districts); mapping of all or parts of six districts as part of operational or epidemiological research by Kenyan Medical Research Institute (KEMRI); AMKENI-INTRAH project aimed at developing client-centred, community-based integrated family planning, reproductive health and child survival services in two of Kenya's provinces, Western and Coast in 2002-03; and supplementary data from various partners who were able to position health facilities on our behalf as they were working at district levels (e.g. Médicins Sans Frontiere (MSF) and the German Technical Cooperation-Deutsche Gesellschaft für Technische Zusammenarbeit (GTZ)). Overall 50% (35/70) districts had GPS coordinates for part or all the service providers in the district.

Hand-drawn maps: Sixteen districts have had their health facilities positioned on hand-drawn maps during an exercise to support the Division of Primary Health Care (DPHC) in 1996-98, with financial support from the United Nations Population Fund (UNFPA). Whilst paper maps were provided to the DPHC, the consulting firm withheld coordinate data. The District Departmental Heads of various ministries prepared the District Development Plans (DDPs) in 1997 under the co-ordination of the District Commissioner (DC) assisted by the members of the District Planning Unit. Fifty two of 57 DDPs contained maps of health facilities, copies of which were obtained from the Ministry of Planning and National Development. Five districts were visited in 1998 by a consulting firm recruited by the Japanese International Cooperation Agency (JICA) for the MoH who produced hand-drawn maps of the locations of health facilities in this part of Western Kenya. All three sources of health facility maps (DPHC, DDP and JICA) were used to identify the spatial coordinates through a process of on-screen digitising (OSD) using Arcview (Version 3.2, ESRI Inc., USA) by re-positioning facilities in accordance with major landmarks, administrative boundaries and relative positions to one another.

1:50,000 scale topographical maps: During the 1950s the British Overseas Survey Department produced topographical maps of the whole of Kenya. Following a number of revisions, largely during the 1970s and 1980s, there are now over 800, 1:50,000 scale maps of Kenya. The maps provide details of major settlements, roads, topographical features such as rivers, forest and parks and the positions of major schools and health facilities, usually only those that are established health centres. These maps have been used to identify the grid reference longitude and latitudes of facilities not geo-positioned using GPS or through OSD of facilities covered by the DSA, DDP or JICA surveys.

International Livestock Research Institute (ILRI) village database: names of health facilities were matched to digital databases of village names and market centres created in

2001 by the International Livestock Research Institute (ILRI), Kenya. The co-ordinates of the village were assigned to the health facility if it had identical or phenologically similar name.

The 1999 Kenya sub-location map: Where a health facility's name and district were known but could not be positioned using any of the methods above, the sub-location map was used. If the name of the facility matched that of a sub-location in the district, then the co-ordinates of the centroid of the sub-location was used on the condition that the size of the area of the sub-location was very small (i.e. 80 km^2). The average sublocation area in Kenya is 87 km^2.

5.2.3 Basic description of the NHSD coverage

The MoH-HMIS list of facilities, which was the primary MoH source that was used to begin the Nation Health Service Database (NHSD), contained 3,924 health facilities of which 1,783 were run by the MoH, 811 by Mission/NGO, 99 by Local Authorities (LA) and 1,231 by the private sector. The other lists that were used to improve incrementally the MoH-HMIS database contained different numbers of facilities, in the decreasing order of FPLM (3,211), KG (2,808), KSPA survey list (2,192), KMD (938), telephone directories (918), Division of Primary Health Care (DPHC) list (732) and the mission sector lists from CHAK (192) (Table 5.2). One hundred and forty two (7%) GoK-MoH health facilities found on these lists were not on the MoH-HMIS database.

Following 3 years of compiling various facility lists and checking on completeness, duplications and positions, the final database contained a total of 6,496 health service providers (Table 5.3). The search did not include mobile clinics, community pharmacies or village health posts, which represent a dynamic and transient grouping of lowest level service providers subject to NGO or DHMT resources and support. The list did attempt to include private sector providers, a prolific grouping of health facilities widely used by the community but difficult to regulate by the MoH.

Table 5.2 Number of general public health facilities in each nationally available public domain list by service provider

Agency	Number of facilities							
	HMIS	FPLM	KG	KSPA	TD	KMD	DPHC	CHAK
MoH	1783	1594	1540	1149	246	82	425	0
Mission/NGO	811	585	560	393	67	53	151	188
LA	99	61	77	60	1	39	14	0
Private	1101	903	548	554	588	761	128	0
Employers	130	68	83	36	16	3	18	0
Total	3924	3211	2808	2192	918	938	736	192

HMIS = Health Management Information Systems (2001); FPLM = Family Planning and Logistics Management (1998); KG = Kenya Gazette (1998); KSPA =Kenya Service Provision Assessment (1999); TD= Telephone Directory (2002); KMD= Kenya Medical Directory (2000); DPHC= Division of Primary Health Care (2002); CHAK= Christian Health Association of Kenya (2000)

The private sector facilities account for 3,049 (47%) of service providers, made up of 2,593 health facilities that provide general clinical services or specialist care, such as maternity and nursing homes (Table 5.3). These were principally identified through the KMD, FPLM, telephone directory and KSPA providing 67% of all private health facilities while the formal MoH-HMIS list contributed only 16% of private health facilities not found from the other sources. This sector has grown rapidly following the decision by the MoH in 1980s to allow clinical officers and nurses employed by the government to engage in private practice (Owino, 1997). This sector further expanded with the rise in unemployment of nurses and clinical officers since the late 1990s.

Table 5.3 Total number of health facilities identified in Kenya by type and service provider[a]

	MoH	*Mission /NGO*	*Local Authority*	*Employers and other ministries*	*Private*	*Total*
Hospitals[b]	129	88	0	0	101	**318**
Health centres[c]	479	142	51	0	21	**693**
Dispensaries	1433	814	42	0	241	**2,530**
Unspecified clinics[d]	0	0	0	0	2230	**2,230**
Specialist facilities[e]	47	61	7	154	456	**725**
Total	**2,088**	**1,105**	**100**	**154**	**3,049**	**6,496**

a. A total of 41 facilities were identified on the national HMIS list but could not be identified according to service provider and/or facility-type.

b. Includes provincial, district, sub-district hospitals or unspecified private hospitals offering general in-patient clinical services.

c. Includes all health centres, sub-health centres and rural health training centres as specified on national databases.

d. Includes all clinics that were not classified in the private or employer sectors that provide generalized health services but were not classed as dispensaries or health centres.

e. Includes all hospitals that provide treatment for only special diseases such as leprosy, tuberculosis, cancer, ophthalmology, spinal injury etc and the large number of maternity and nursing homes.

Among the four districts described in Section 2.3, where the author actively sought service providers in collaboration with informed people at the district level, 50% of private sector providers were not recorded on any official centrally held lists. Of 38/70 districts where there was a comprehensive survey by the author or the DHMTs reviewed the lists provided to them, 482 private sector formal health service providers (31% of the private or 18% of all health facilities in these districts) were identified that were not centrally available (Table 5.4). It would therefore appear that reliance upon nationally available lists of private service providers results in a grossly inadequate coverage of this sector. Even at the district-level DHMTs may not be aware of all private practitioners and as such this sector remains poorly defined and hard to regulate.

Table 5.4 Deletions (unshaded columns, n= 31), and additions (shaded column, n= 721) of centrally constructed database following district reviews

	Number of facilities						
Agency	HMIS	FPLM	KG	KSPA	TD	KMD	DHMT
MoH	2	1	0	0	0	0	165
Mission/NGO	1	0	2	0	0	1	72
LA	0	0	0	0	0	0	1
Private	4	1	7	1	1	10	482
Employers	0	0	0	0	0	0	1
Total	7	2	9	1	1	11	721

The formal missions and NGO sectors represent the third largest health service provider after the private and GoK-MoH sector. The NHSD contained 1,105 (17%) mission/NGO health facilities of which 1,044 offer general clinical services (Table 5.2 & 5.3). Only 9% of the mission/NGO health facilities in the NHSD were not on any of the centrally held lists and were captured at the district level. While some of the resources to this sector are partial grants from the MoH, these have diminished over the years as the MoH's budgetary allocation has dwindled. As such, the sector's resource allocation decisions are not significantly influenced by MoH budgetary provisions. The distribution of the mission health services is largely determined by the religious inclination of the target population, in Kenya this sector is dominated by Christian denominations. A good example of its manifestation is in that Turkana district in Rift Valley Province had 50 mission health facilities compared to 34 GoK-MoH. However, the whole of the three districts in North Eastern province, which is predominantly Muslim, had seven mission to 61 GoK-MoH health facilities.

A fourth sector that provides health services to the general public is the Local Authority (LA). The LA services are located in major municipalities and are managed by a Medical Officer of Health appointed by the Ministry of Local Government (MLG). Although some of the medical personnel are seconded to this sector by the MoH, the bulk of resources are provided by the MLG. In the NHSD there were 100 (1.5%) LA health facilities, 93 of which provide general clinical services (Table 5.3). Another important source of health care in Kenya is the informal sector made up of shops, pharmacies and traditional healers. These have not captured in the study and are probably beyond the scope of a national HMIS-GIS system.

In the following descriptive analysis of the completeness and coverage of facility locations, the focus is on the GoK-MoH formal health facilities that provide clinical services to the general public and whose resource allocation is primarily determined by the GoK-MoH. Specialist services such as maternity and nursing homes, ophthalmic centres, tuberculosis, oncology and other specialist investigation centres have not been included. In addition service providers located among the industrial, agricultural and education sectors, and those run by or on behalf of the armed, prison and other Government services have been excluded. These services are provided to targeted employed populations and their immediate families and hence are not accessible to the general public. In total 47 specialist, institutional and employer health facilities were not included in the analysis. The final GoK-MoH public sector general clinical service provider list contained 2,041 (31%) health facilities (Table 5.3 & 5.5).

Table 5.5 Coverage of health services by province

Province	*GoK-MoH*	*Mission/ NGO*	*Local Authority*	*Specialist facilities, employers and other ministries*	*Private*	*Total*
Central	295	120	0	69	249	**733**
Coast	213	88	20	99	338	**758**
Eastern	348	226	0	48	421	**1043**
Nairobi	26	50	60	154	588	**878**
N. Eastern	61	12	0	13	45	**131**
Nyanza	282	131	9	113	360	**895**
Rift Valley	658	303	4	166	411	**1542**
Western	158	114	0	63	181	**516**
Total	**2,041**	**1,044**	**93**	**725**	**2,593**	**6,496**

Special surveys by donors, NGO's or research groups in selected districts provided an opportunity to examine the likelihood that the centrally available listings would not identify a GoK-MoH service provider at the district level. These have been narrowed down to five districts (Bondo, Greater Kisii, Kwale, Makueni, Kilifi) that formed part of detailed GIS studies described in Chapters 3 and 4 and research studies undertaken in Kilifi district by colleagues at the Kenya Medical Research Institute (KEMRI-Kilifi- unpublished data). Among these districts a total of 16 (8%) out of 202 GoK-MoH health facilities were identified that were not on centrally held lists and databases. These were Bondo (2), Greater Kisii (4), Kilifi (1), Kwale (3) and Makueni (6). These represented an average of 3 omissions per district. A less active comparison was possible following the returns of 32/69 district lists and maps from DHMT's in 2004. These lists resulted in a number of deletions and identified some additions. In summary, 3 GoK-MoH health facilities in two (MoH-HMIS, FPLM) of the eight formal lists were deleted following verification either through active field visits by the author or response from districts (Table 5.4). All of the GoK-MoH health facilities in the other lists were verified as existing and functioning.

However, 721 health facilities, including 165 (8%) of all GoK-MoH health facilities, which were not on any of the existing lists, were captured through active field visits and responses from the DHMTs (Table 5.5). This reflects an important aspect of national database construction, the temporal dimension. The most recent of all the formal available lists was the HMIS-MoH one which was last updated in 2001. While it is likely that some existing health facilities were omitted even when these lists were developed, a significant number could have been established after 2001.

The study showed that 32% of all GoK-MoH public health facilities were in Rift Valley province followed by Eastern (17%), Central and Nyanza each with 14%, Coast (10%), Western (8%), Nairobi (2%) and North Eastern (3%) (Table 5.5). Although there were clear disparities in the number of MoH public health facilities between some of the provinces, these need to be checked against the distribution of population before any judgment on the equity of health care provision is made (Section 5.3.3).

In terms of the annual rate of growth of public health facilities in the period 1959-2004, North Eastern province had the highest rate with 7.1% and the lowest was in Coast at 3.3%. However, in absolute terms the number of health facilities in North Eastern and Nairobi province increased by the least amount (70 health facilities each), while the largest rise was in Rift Valley with an additional 901 (Table 5.6).

Thirty-eight out of 70 (54%) districts were comprehensively covered either through field surveys by the author or correspondence with the DHMTs. Nineteen districts were partially covered with the help of partners and colleagues, while health facility data for 12 districts had not been verified or updated with feedback from the DHMTs by June 2005 (Table 5.7). In some districts there was more than one partner involved in similar activities resulting in duplication of the mapping efforts (Table 5.8).

Table 5.6 Rate of growth[a] of public health facilities in the period 1959-2004

Province	**P_{1959}**	**P_{2004}**	**e^{rt}**	**$rt=\log(e^{rt})$**	**t**	**R**
Central	37	415	11.22	2.42	45	5.4
Coast	67	301	4.49	1.50	45	3.3
Eastern	53	574	10.83	2.38	45	5.3
Nairobi	6	76	12.67	2.54	45	5.6
NorthEastern	3	73	24.33	3.19	45	7.1
Nyanza	53	413	7.79	2.05	45	4.6
Rift Valley	60	961	16.02	2.77	45	6.2
Western	34	272	8.0	2.08	45	4.6
Total	313	3,085	9.86	2.29	45	5.1

a. The average annual growth rate of public health facilities the period 1959-2004 was produced for each province using the following equation; $P_{2004}=P_{1959}\ e^{rt}$, where P_{2004} is the number of public health facilities in 2004, P_{1959} is the number of public health facilities in 1959, t is the number of years between year 1959 and 2004, and r is the average growth rate.

Table 5.7 Extent of the coverage of NHSD development work

Province	Districts with complete survey by author and colleagues [a]	District with response from DHMTs [b]	District with partial coverage by author, colleagues and partners [c]	Districts not covered [d]	Total districts
Central	0	3	2	2	7
Coast	2	1	4	0	7
Eastern	1	8	3	1	13
Nairobi	0	0	1	0	1
North Eastern	0	0	2	2	4
Nyanza	3	4	2	3	12
Rift Valley	0	11	2	5	18
Western	0	5	3	0	8
Total districts	**6**	**32**	**19**	**13**	**70**

a. These are the author's four study districts-Bondo, Kwale, Makueni, Greater Kisii (Central Kisii and South Kisii), and Kilifi district in which other KEMRI/WTRL scientists have worked.

b. These are districts where DHMTs have responded fully and have returned updated lists and maps. They are; Central (Maragua, Muranga, Nyandarua), Coast (Malindi), Eastern (Embu, Isiolo, Marsabit, Mbeere, Meru Central, Meru North, Meru South, Tharaka), Nyanza (Homa Bay, Migori, Nyando, Suba), Rift Valley (Baringo, Buret, Kajiado, Keiyo, Kericho, Nandi, Narok, Samburu, Trans Mara, Trans Nzoia, West Pokot) and Western (Butere/Mumias, Lugari/Malava, Mt. Elgon, Teso, Vihiga).

c. These are districts covered to varying degrees by KEMRI/WTRL and partners and for which there is no response from the DHMTs. They are; Central (Kiambu, Nyeri), Coast (Lamu. Mombasa, Taita Taveta, Tana River), Eastern (Kitui, Machakos, Mwingi), Nairobi (Nairobi), North Eastern (Garissa, Wajir), Nyanza (Rachuonyo, Siaya), Rift Valley (Bomet, Nakuru) and Western (Bungoma, Busia, Kakamega)

d. These are districts that have not been covered at all and they are; Central (Kirinyaga, Thika), Eastern (Moyale), North Eastern (Mandera), Nyanza (Kisii North, Kisumu, Kuria), Rift Valley (Koibatek, Laikipia, Marakwet, Turkana, Uasin Gishu).

Table 5.8 Districts covered by partners[a]

Province	Total Number of districts	Districts with one partner	District with >1 partner
Central	7	0	0
Coast	7	4	3
Eastern	13	8	0
Nairobi	1	0	0
North Eastern	4	0	0
Nyanza	12	2	0
Rift Valley	18	4	0
Western	8	3	3
Total districts	**70**	**21**	**6**

a. These partners are KEMRI/KILIFI, AMKENI/UNC, DANIDA, MoH-DFH/UNFPA, MoH-DSA/UNICEF, KEMRI/CDC, DANIDA, TRANS-MARA DEV. PROG.

5.2.4 Spatial description of the NHSD

It was possible, through a combination of approaches (Section 5.2.2), to spatially position 1,991 (98%) of the public GoK-MoH in the NHSD, 917 (88%) of the Mission/NGO, 73 (78%) of the LA, 1,356 (52%) private general service providers and 509 (70%) specialist service providers and those supported by institutions and employers. The majority of the combined facility positions (43%) were identified through the use of on-screen digitising (OSD) from hand drawn maps provided by various partners and MoH and DHMT initiatives. Additional locations were directly positioned using GPS coordinates (30%), 10% from 1:50,000 maps, 11% from International Livestock Research Institute (ILRI) village databases and 6% from centroid positions of small sub-locations. Overall 3% of general clinical service providers within the GoK-MoH sector could not be positioned by any approach available outside of the direct consultation with district health management teams (Table 5.9).

Table 5.9 Numbers of facilities spatially defined using different positioning methods.

Agency	Source of co-ordinates						
	GPS	1:50000 maps	Handrawn maps*	Village digital database*	Centroids of sub-locations*	Not positioned	**Total**
MoH	509	305	1046	38	93	50	**2,041**
Mission/NGO	154	75	438	166	84	127	**1,044**
LA	51	2	11	7	12	10	**93**
Private	580	44	391	255	86	1,237	**2,593**
Other**	151	41	183	98	36	216	**725**
Total	1,445	467	2,069	564	311	1,640	6,496

* Spatial information from these sources was captured through on-screen digitising (OSD).
** 'Other' is made up of specialist facilities from all sectors, Institutional and Employer health facilities.

All GoK-MoH health facilities in Western and North Eastern provinces were positioned. Eastern and Central province had 99% of all GoK-MoH health facilities positioned, followed by Rift Valley (97%), Coast and Nyanza each with (95%) and Nairobi with 81%. Of all GoK-MoH general public health facilities mapped using GPS, Nairobi province had the highest proportion (95%), followed by the Coast (77%), Western (63%), Nyanza (30%), Eastern (15%), Central and Rift Valley (11%). No health facility in North Eastern province was positioned using GPS (Table 5.10). The spatial distribution of the health facilities nationwide by service provider and by type are shown in Figures 5.2-5.5.

Table 5.10 Number of GoK-MoH health facilities spatially defined by province

Province	Source of co-ordinates						
	GPS	1:50000 maps	Hand drawn maps	Village digital database	Centroids of sub-locations	Not positioned	**Total**
Central	31	133	125	3	1	2	**295**
Coast	156	3	24	11	9	10	**213**
Eastern	51	80	206	3	5	3	**348**
Nairobi	20	0	0	0	1	5	**26**
North Eastern	0	21	35	1	4	0	**61**
Nyanza	82	20	146	4	17	13	**282**
Rift Valley	70	40	464	15	52	17	**658**
Western	99	8	46	1	4	0	**158**
Total	**509**	**305**	**1,046**	**38**	**93**	**50**	**2,041**

Figure 5.2 A provincial map of Kenya showing the location of GoK-MoH health facilities (n=1,991/2,041)

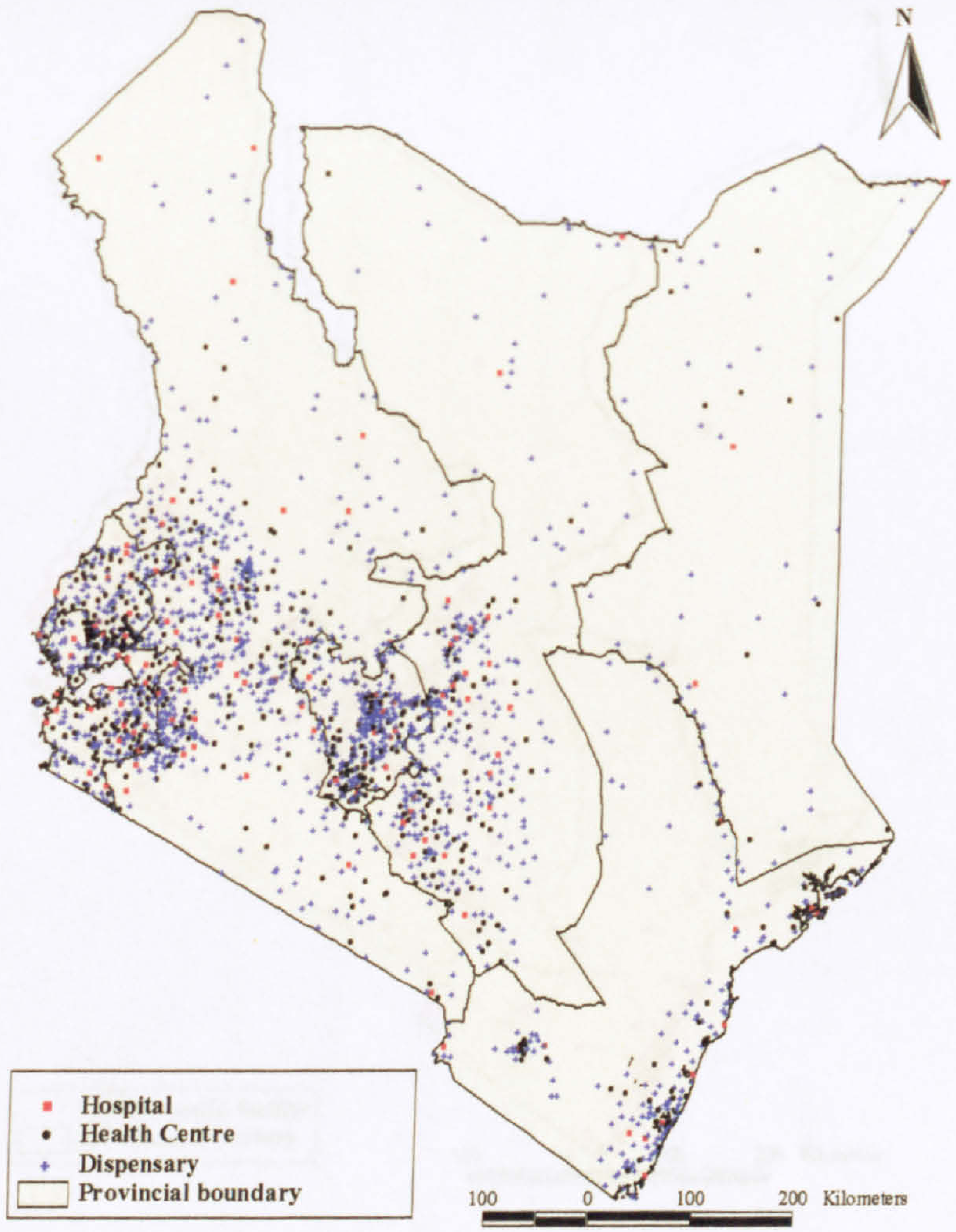


Figure 5.3 A provincial map of Kenya showing the location of mission/NGO and LA health facilities by facility type (n=1,000/1,137)

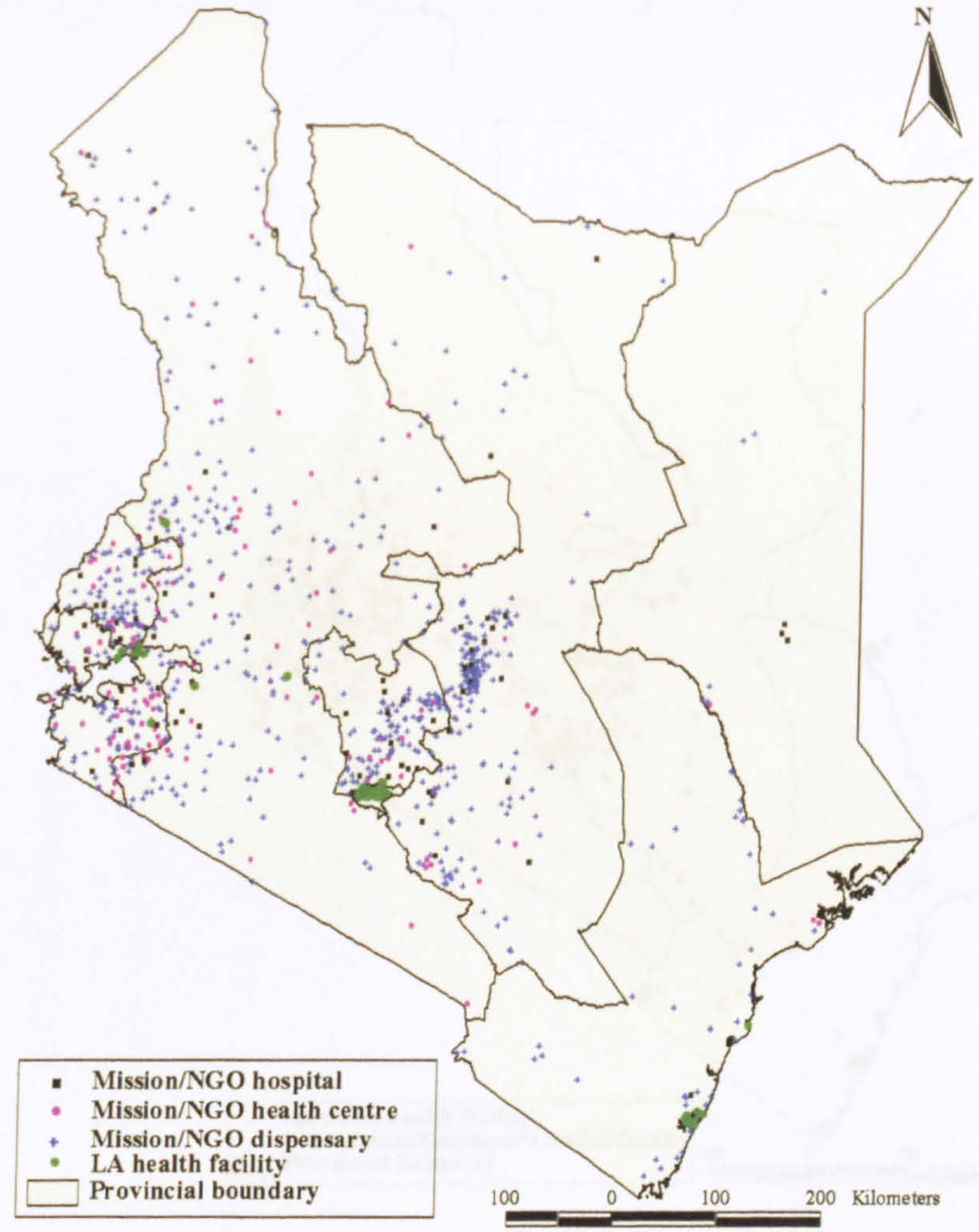


Figure 5.4 A provincial map of Kenya showing the location of private health facilities (n=1,356/2,593)

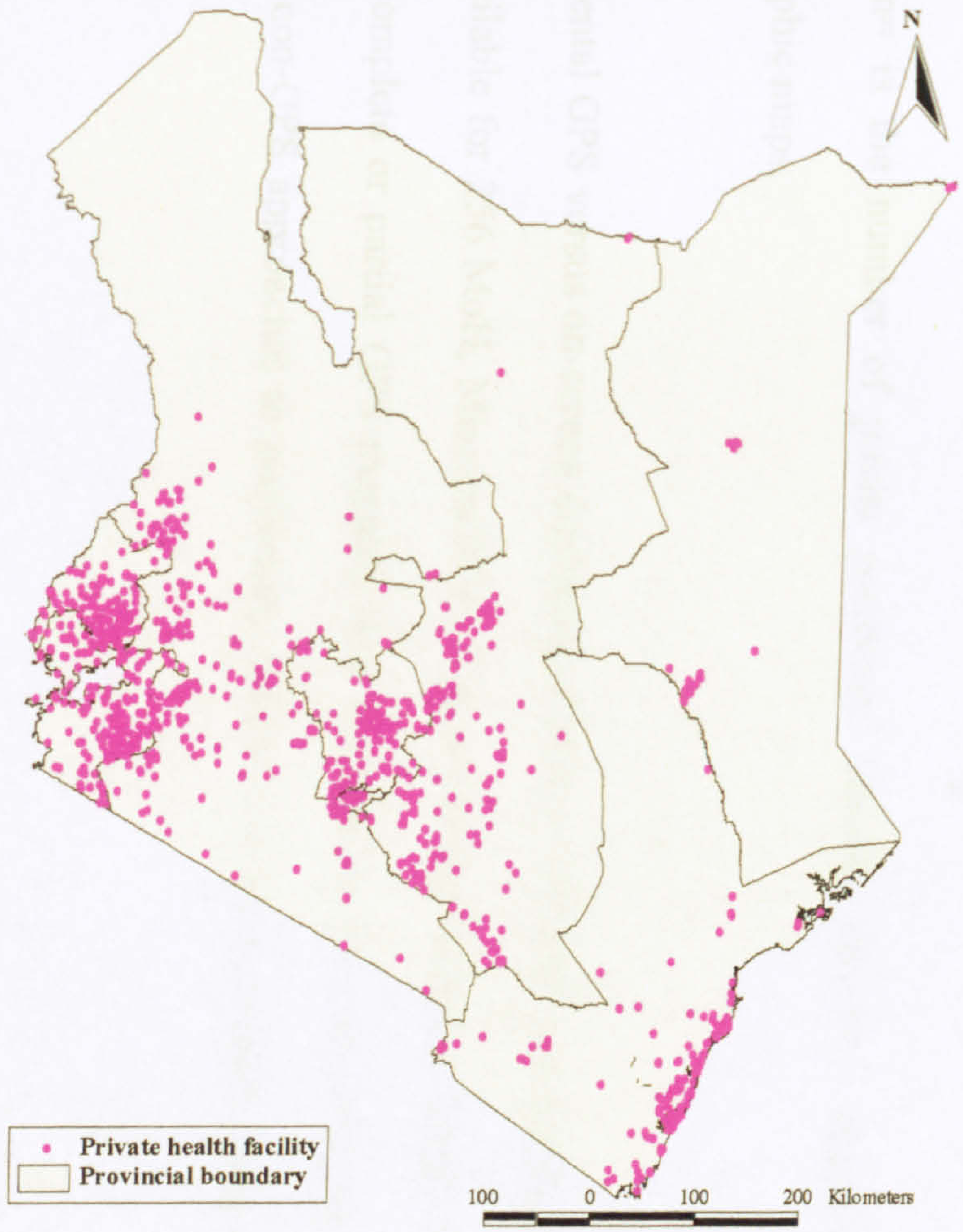
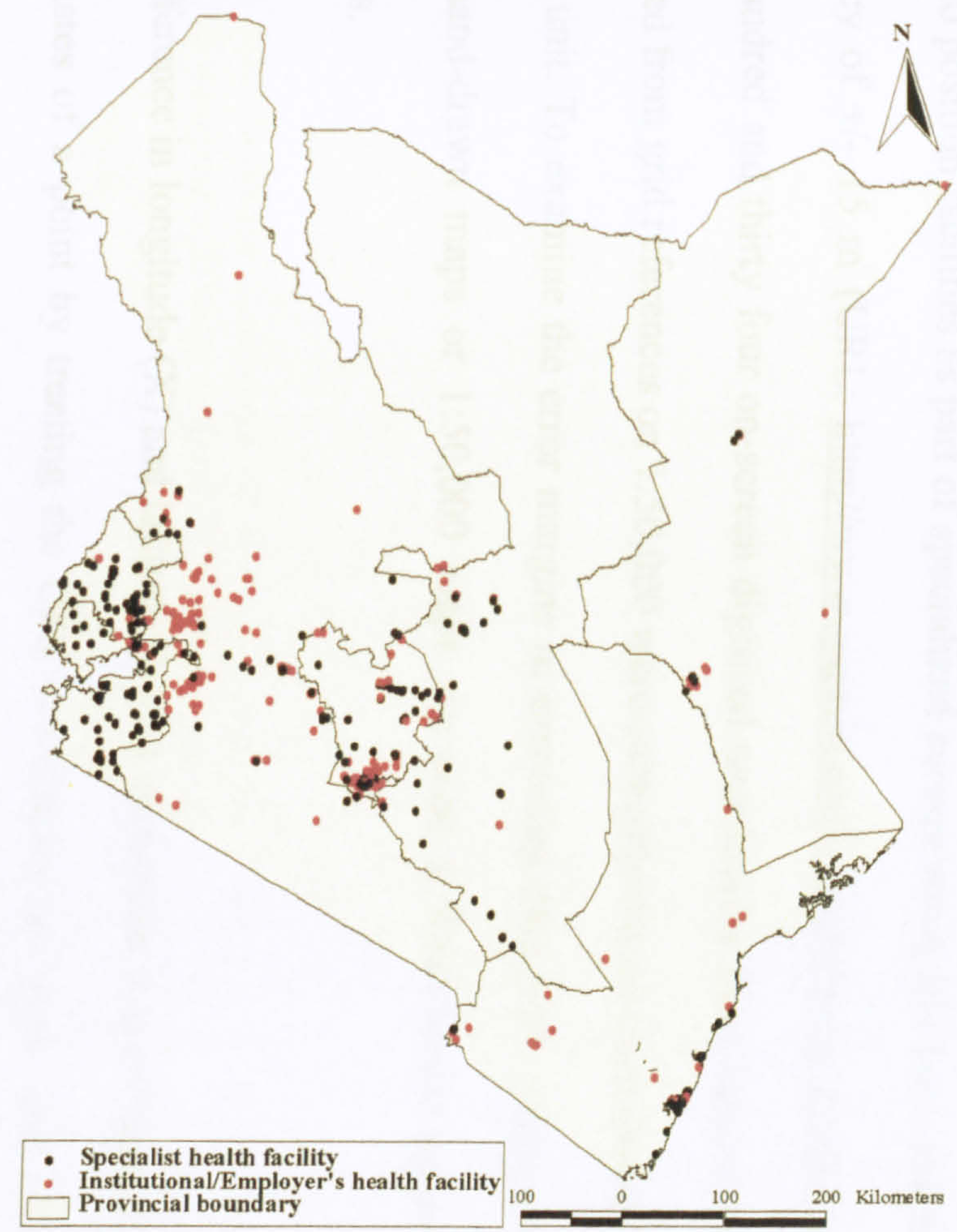


Figure 5.5 A provincial map of Kenya showing the distribution of specialist, institutional/employer health facilities (509/725)



5.2.5 Testing the accuracy of the non-GPS methods of health facility mapping

Most handheld GPS units used from 1st May 2000 (when *selective availability* was lifted by USA) to position facilities as part of specialized survey work will have had an estimated mean accuracy of +/- 15 m (URL: http://www.garmin.com; http://www.trimble.com; Hay, 2000). One hundred and thirty four on-screen digitised coordinates from hand drawn maps and 125 extracted from grid references on 1:50,000 were subsequently or coincidentally positioned with a GPS unit. To examine the error margins in extracting data from either on-screen digitising from hand-drawn maps or 1:50,000 maps we used a Root-Mean Square Error (RMSE) analysis.

The difference in longitude (X) and latitude (Y) for each point was computed from each pair of coordinates of a point by treating the GPS coordinates as 'truth' and compared on-screen digitised and 1:50,000 coordinates. The shift at each point was then computed as the square root of the sum of the square of X and Y. This shift was considered to be the difference between the known and observed position of the point. The RMSE was then computed using the formula:

$$\mathrm{RMSE} = \frac{\left(\sum \sqrt{(X^2 + Y^2)}\right)}{n}$$

where n= is the number of points positioned through on-screen digitising or from the topographic maps.

Coincidental GPS versus on-screen digitising (OSD) or 1:50,000 topographic map referencing was available for 256 MoH, Mission/NGO, LA or private facilities, largely from 29 districts where complete or partial GPS mapping was undertaken. This allowed the accuracy of the various non-GPS approaches to positioning facilities to be examined using RMSE analysis.

The analysis revealed accuracy values of about 1.3 km for on-screen digitising (n = 134) and 1.4 km for 1:50,000 topographic maps (n = 125) (Table 5.11). Overall 65% of on-screen digitising coordinates and more than 80% of the 1:50,000 scale map co-ordinates were within 1 km of the reference GPS readings (Figures 5.6a & b). This implies that 765/1177 and 214/305 GoK-MoH general public health facilities mapped using OSD or 1:50,000 maps respectively were positioned at an accuracy of 1km or less. If the GPS positioned health facilities were added to these, a total of 1,488/1991 (75%) mapped public GoK-MoH facilities were within 1 km accuracy.

Table 5.11 Accuracy assessment of on-screen digitising (OSD) from hand-drawn maps and use of 1:50,000 topographical maps against GPS positioning.

Method	No. of facilities (n)	$\sum(r) = \sum\sqrt{(x^2 + y^2)}$	RMSE= $\sqrt{[\sum(r)/n]}$
1: 50000	121	240.4914	1.387058
On-Screen digitising (OSD)	134	239.8689	1.337934

Figure 5.6a Distance (km) of the OSD-ordinates from their reference GPS co-ordinates

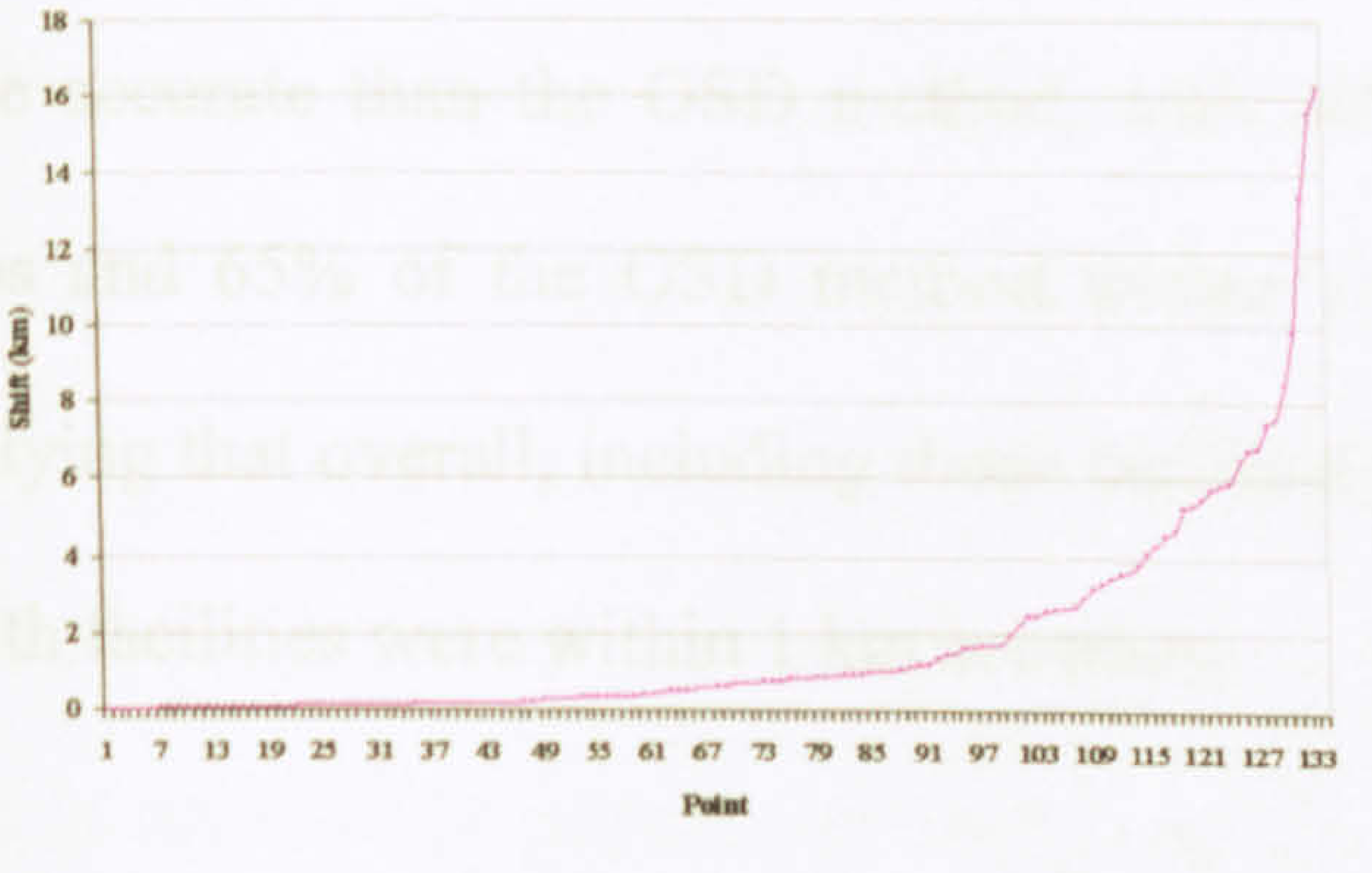
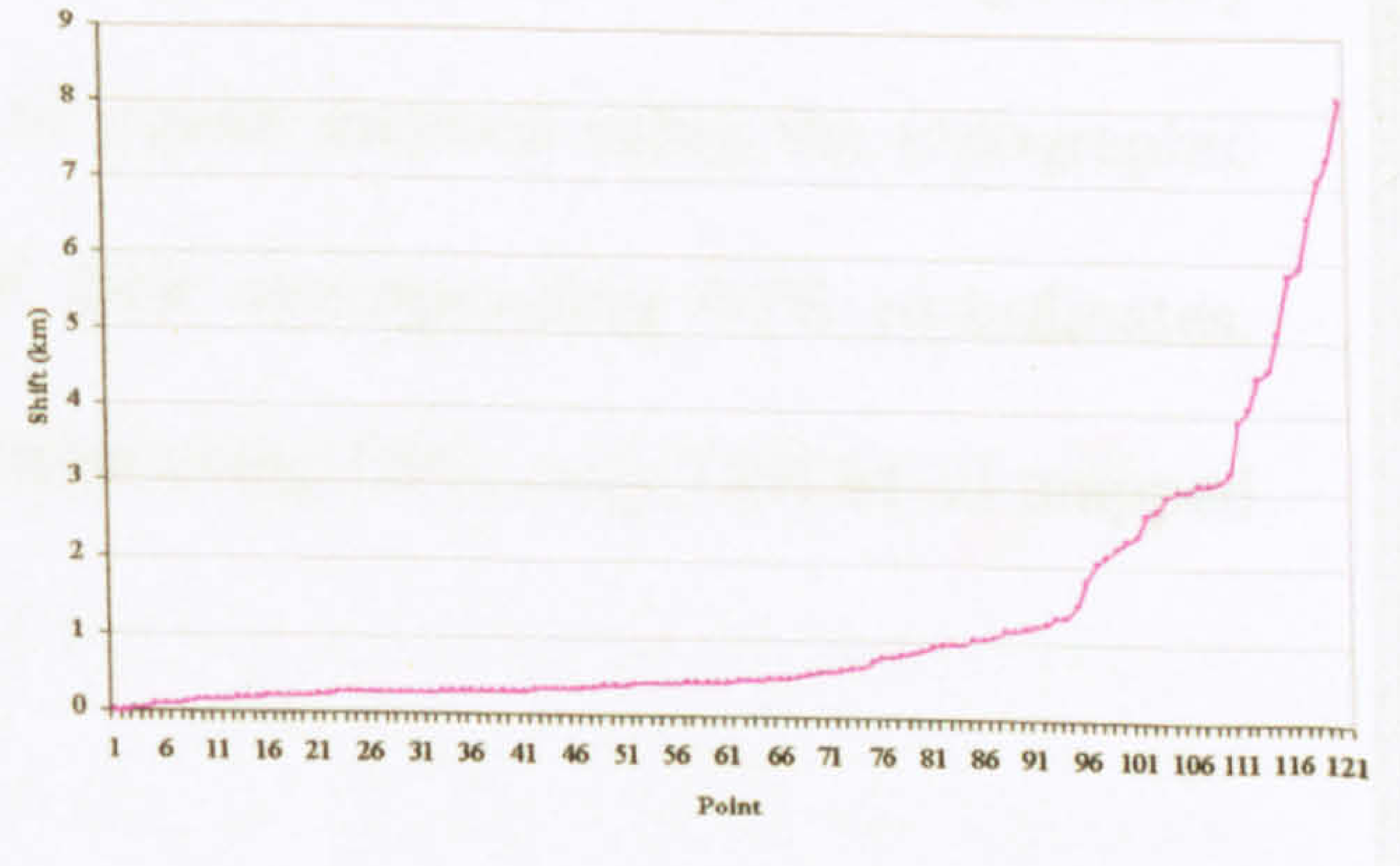


Figure 5.6b Distance (km) of the 1:50,000 scale map co-ordinates from their reference GPS co-ordinates



5.2.6 Summary of the NHSD accuracy and coverage

The focus of the work done in previous two chapters was to develop spatial accessibility models for GoK-MoH health services. This sector is nationally the most comprehensively covered and accurately mapped. Even so, confirmation of the existence and operational status of health facilities has been done for only 38/70 districts for which response to correspondence with DHMTs has been received, comprising 48% of all government health facilities in the database. For the remaining 32 districts one cannot be certain of the exact numbers of GoK-MoH health facilities, probably the same for the mission/NGO sector and certainly the private health facilities considering that for those districts that responded, about half of the private facilities were not on any formal list. Nonetheless, these districts contributed 52% of the GoK-MoH health facilities in the NHSD. Of all the GoK-MoH health facilities in the NHSD, 98% were mapped. While all health facilities in the four study districts were positioned using GPS, only 25% have been positioned nationally using this method. As described in Section 5.3.2, 14% and 58% of the mapped health facilities nationally were captured from 1:50,000 scale maps or through OSD respectively, while 2% were not mapped at all. The accuracy of coordinates derived from 1:50,000 scale maps or through OSD were ±1.4 km and ±1.3 km respectively compared to the GPS co-ordinates as presented in Table 5.11. However, between the two non-GPS sources of coordinates, the 1:50,000 topographic scale maps were generally more accurate than the OSD method, with 80% of all points mapped using the topographic maps and 65% of the OSD method within 1 km of their corresponding GPS co-ordinates. Implying that overall, including those facilities positioned using GPS, only 75% of all mapped health facilities were within 1 km accuracy.

When only the 38 districts with complete coverage were considered, only 75% of all GoK-MoH health facilities, including those positioned with GPS, were mapped with an accuracy of

1 km or less. Nationally, there was an unequal coverage between districts in the number of health facilities mapped using any of the three methods. Several districts were poorly represented with 42 districts having more than fifty-percent of their health facilities mapped using the lower OSD method. Overall, at the national level, the GoK-MoH formal health service component of the database includes a significant number of health facilities that were not mapped to appropriate accuracies, over 9% remain not positioned and an unknown number, estimated at 6% considering the number of districts where the DHMTs fully responded, are not on the database at all.

5.2.7 Implications for scale-up of access models to the national level

Despite the enormous efforts invested in developing the NHSD one can still not be certain that the universe of all functioning health facilities in the country has been captured, although one can more confidently assert that the database contains the majority of the GoK-MoH health facilities, but this still may have omitted about 15% of facilities (9% not positioned and 6% probably not on the database). Even if this level of coverage was acceptable in scaling-up the models, only 75% of the government health facilities in the database have been positioned within 1 km accuracy. In Chapter 4, the importance of adjusting the access models for patients' actual use of health services of different types was discussed. Briefly, when any two adjacent health facilities were considered, the catchment boundary between them displaced in favour of the higher order facility. However, an important implication of the low spatial accuracy of the national database of government health services is that any models used at the national level cannot be adjusted for the varying patients drawing capacities of facilities of different types. This is because the adjustment factors are heavily dependent on the accuracy of the health facility position.

To illustrate this, in Greater Kisii district, two health facilities of different types (Boige dispensary and Ogembo district hospital) were isolated from the rest of the health facilities. A horizontal positive error of 1 km was introduced to the positions of the two health facilities, roads and other input data and the 'best-fit' model was implemented. The model was then implemented with only the health facilities positions incorrect, while other input data remained in their true position. Figure 5.7a compares the unadjusted boundaries of the correct health facility positions with the erroneous ones. Figure 5.7b shows the adjusted boundaries of the correct against the displaced input data. Figure 5.7c a three-way comparison of the adjusted boundaries when all input data had a 1 km error to when only the coordinates of the health facilities had this error. Both incorrect adjusted boundaries were then compared to the correct adjusted boundaries.

From Figure 5.7a it is clear that even before adjustment, the shift of 1 km in true position of the input data results in a shift of facility boundaries equivalent to the amount of error in position but the outline of the boundaries remain the same in appearance. Similarly, after adjustment the boundaries still maintain the same amount of displacement but there is no distortion in the appearance of boundaries, this is because all input data had the same amount of error before and after adjustment.

To tease out what happens when only the health facilities have a +1 km horizontal error, the other input data such as roads, rivers and elevation were maintained in their true spatial position and the model was implemented with error only in the health facilities' coordinates (Figure 5.7c). When the two incorrect adjusted boundaries were compared to the true adjusted boundaries, they were both displaced by almost the same margin while there was no significant variation in the shape of the catchment between the adjusted incorrect boundaries (Figure

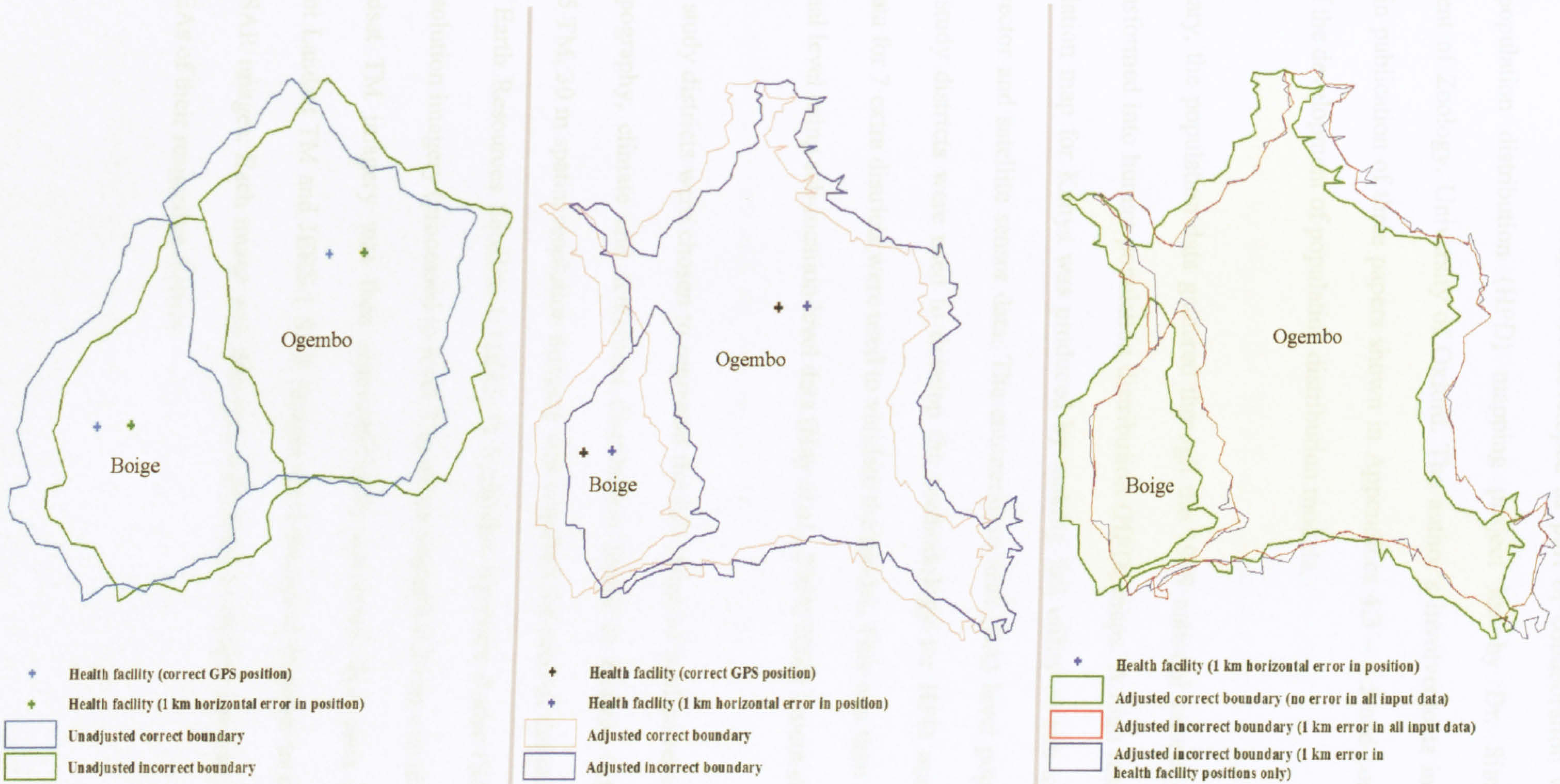
5.7c). From this experiment it appears that the main contributor to the appropriateness of adjusting health facility catchments is the accuracy of the coordinates themselves. The degree to which other input data influence the adjustment of boundaries will probably vary depending on the strength of these inputs in defining the distance between health facilities and in hindsight it might have been more appropriate to carry out sensitivity analysis in terms of model outcomes and with respect to all inputs by simulating different data scenarios. Nonetheless, the example is aimed at showing the importance of accurate coordinates of health facilities, without which the process of adjusting health facility catchments for actual use introduces an artificial and inappropriate level of accuracy.

Figure 5.7 The effect of a 1 km error in position of health facilities on adjustment of catchment boundaries of adjacent facilities of different types

a) unadjusted correct boundaries versus unadjusted incorrect boundaries (all input data have 1 km error)

b) adjusted correct boundaries versus adjusted incorrect boundaries (all input data have 1 km error)

c) adjusted correct boundaries versus adjusted incorrect boundaries (only health facility positions have 1 km error)



5.3 The national map of population distribution

5.3.1 Developing national maps of population distribution

The population distribution maps were developed as part of collaboration with a larger human population distribution (HPD) mapping project led by Dr. Simon Hay of Department of Zoology, University of Oxford. The author's involvements in this project resulted in publication of three papers shown in Appendices 4.3 – 4.5 and contain greater details of the development of population distribution models.

In summary, the population data gathered through the 1999 national census enumeration were transformed into human population distribution (HPD) maps. A high resolution (100 m) population map for Kenya was produced by making full utility of sub-location level census, vector and satellite sensor data. The enumeration area (EA) level population data for four study districts were used to develop the methodology for HPD mapping while similar data for 7 extra districts were used to validate the model. This was then scaled-up to the national level using sub-location level data (Hay *et al.,* 2004; 2005; Tatem *et al.,* 2004).

The four study districts were chosen to represent the full range of land-cover and land-use types, topography, climate and settlement distribution found in Kenya. Ortho-rectified LandSat 5 TM, 30 m spatial resolution imagery was acquired for each of the study districts. Japanese Earth Resources Satellite 1 (JERS-1) Synthetic Aperture Radar (SAR) 12.5 m spatial resolution imagery (processed to level 2.1) of wavelength 0.24 m was also acquired. The Landsat TM imagery was then atmospherically corrected. For each district, the component Landsat TM and JERS-1 SAR images were mosaiced together to create single TM and SAR images. Each image was then geo-registered to images derived from vector polygon EAs of their respective district.

A set of vector points and ancillary data for each district were used for map validation. These included the locations of health facilities, market centres, villages and selected households described in Section 2.4. In addition, 1999 census data at the EA-level and vector layers of roads, rivers, dams and swamps were used. Three different land cover maps of Kenya were also used.

To develop an effective classifier of settlements, an initial testing of parametric, non-parametric, per-pixel and super-resolution classifiers was carried out (Tatem *et al.*, 2004; Tatem *et al.*, 2005). The classifier deemed to be most effective was used to produce settlement maps for each district. For each of the four districts, the point data on market centres, health facilities and schools were utilised in the identification of settlement training sites, and census data were used as a check to ensure a settlement had indeed been identified. Various land cover maps were then used in combination with the census data and GIS layers to identify representative training samples for all non-settlement areas of the four districts. Training samples were only selected where all three land cover maps were in agreement with each other and the census and GIS data, to minimise error and its propagation through the methodology.

The ground-collected set of points (towns and market centres) was used as the principal source of settlement mapping assessment. These points were taken to represent locations of settlements to validate the accuracy with which each classification identified settlement pixels. The satellite sensor image-derived settlement maps were coded into settlement/non-settlement pixels (binary) and the vector-point validation datasets were used to extract pixels for each district and measures of accuracy were calculated using the Kappa statistic. Finally a visual comparison between 1999 enumeration area census counts and settlement maps was made to check for any obvious inaccuracies.

Using the classifiers of settlements and population census information at the sub-location level, nationwide settlement maps for the whole country were developed and transformed to population distribution maps. The satellite image-derived settlement map at 100 m spatial resolution, with the output map showing the percentage of each pixel covered by settlement. Where a settlement or multiple settlements were identified within a sub-location, the population count was areal weighted over the settlement pixels, weighted by the settlement percentage. Areal weighting is a method which simply overlays a regular raster grid on irregular polygon data and assigns population according to the proportion of the polygon area in the raster grid cell. All other pixels in the sub-location were given a zero value. Where no settlements were identified within a sub-location, the population count was simply areal weighted over the entire sub-location.

5.3.2 Result, accuracy and precision

In Chapter 4, the population map used was at the EA resolution while the data input for the national population distribution map was at the sub-location level. In the study districts, a sub-location, on average, had 14 EAs and as such the EA data would probably be as many times higher in resolution. A clear indication of this variation in resolution is probably best depicted in Figures 5.8 a-b, which shows a population map based on EA data and the other extracted from the national population distribution map, presented as one standard deviation from the mean. The EA-based population map shows significant heterogeneity in distribution of population.

For the four study districts the settlement map was shown to have a Kappa value of 0.96 in Bondo, 0.60 in Greater Kisii, 0.92 and 0.57 for Kwale and Makueni respectively (Table 5.12). Population counts at enumeration area (EA) level were available for 11 districts. These were used to determine an indication of population mapping accuracy across the four major ecozones. Additionally, to determine settlement population mapping accuracy, Africover urban class extents with CBS-defined populations assigned to each were available. The EAs provided an approximate indication of how well populations had been distributed within sub-locations.

Table 5.12 Overall RMSEs of the national population distribution map for each of the 11 districts

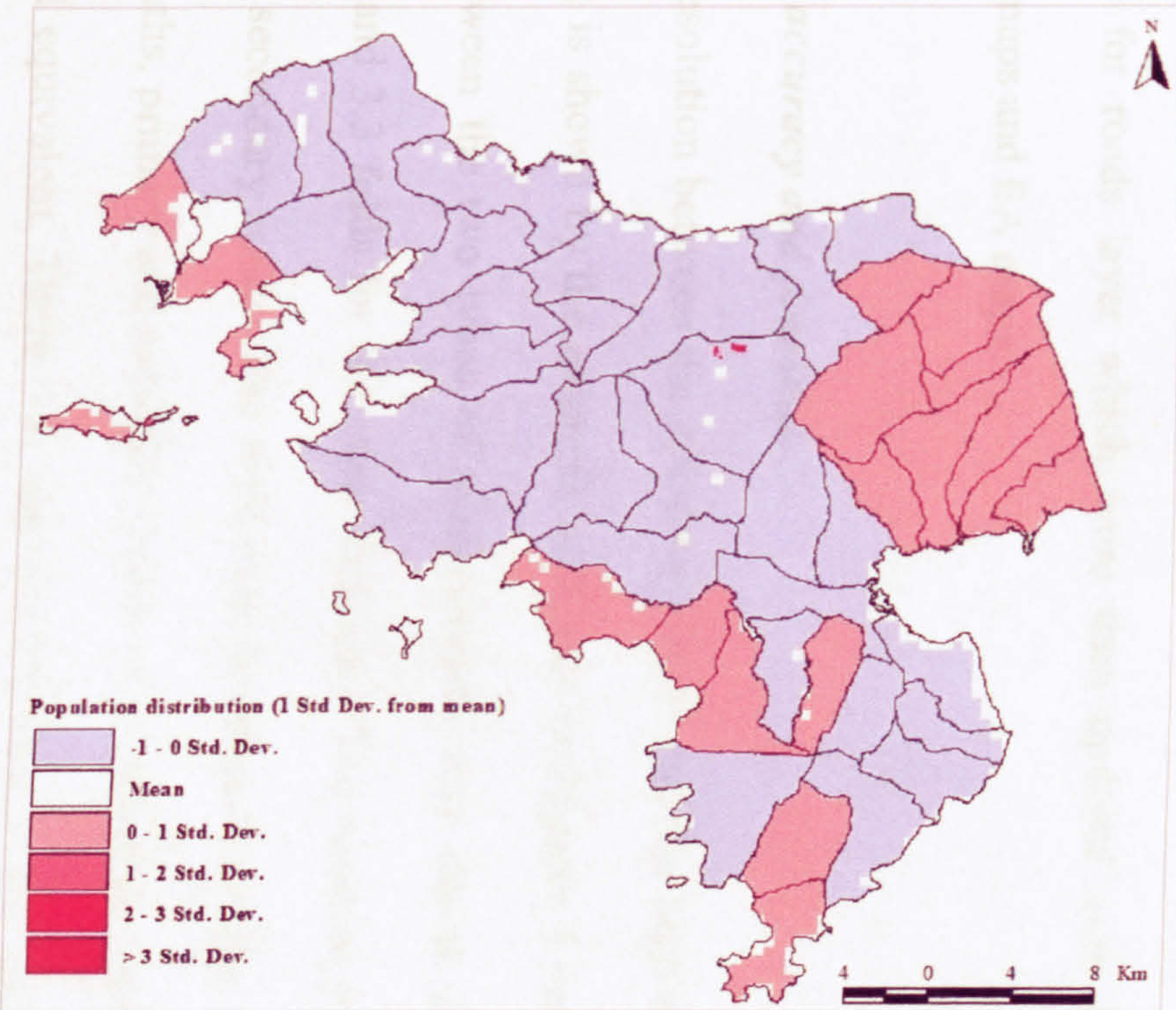
District	RMSE of the national population map	Kappa values for settlement map
Bondo	281.0716	0.96
Wajir	220.8628	
Nakuru	950.4096	
Malindi	694.4537	
Makueni	288.1023	0.57
Kwale	531.5942	0.92
Greater Kisii	288.5923	0.60
Kirinyaga	355.1373	
Kilifi	472.8693	
Homa Bay	341.2478	
Busia	296.2399	

5.3.3 Implications for scaling-up the accessibility model to the national-level

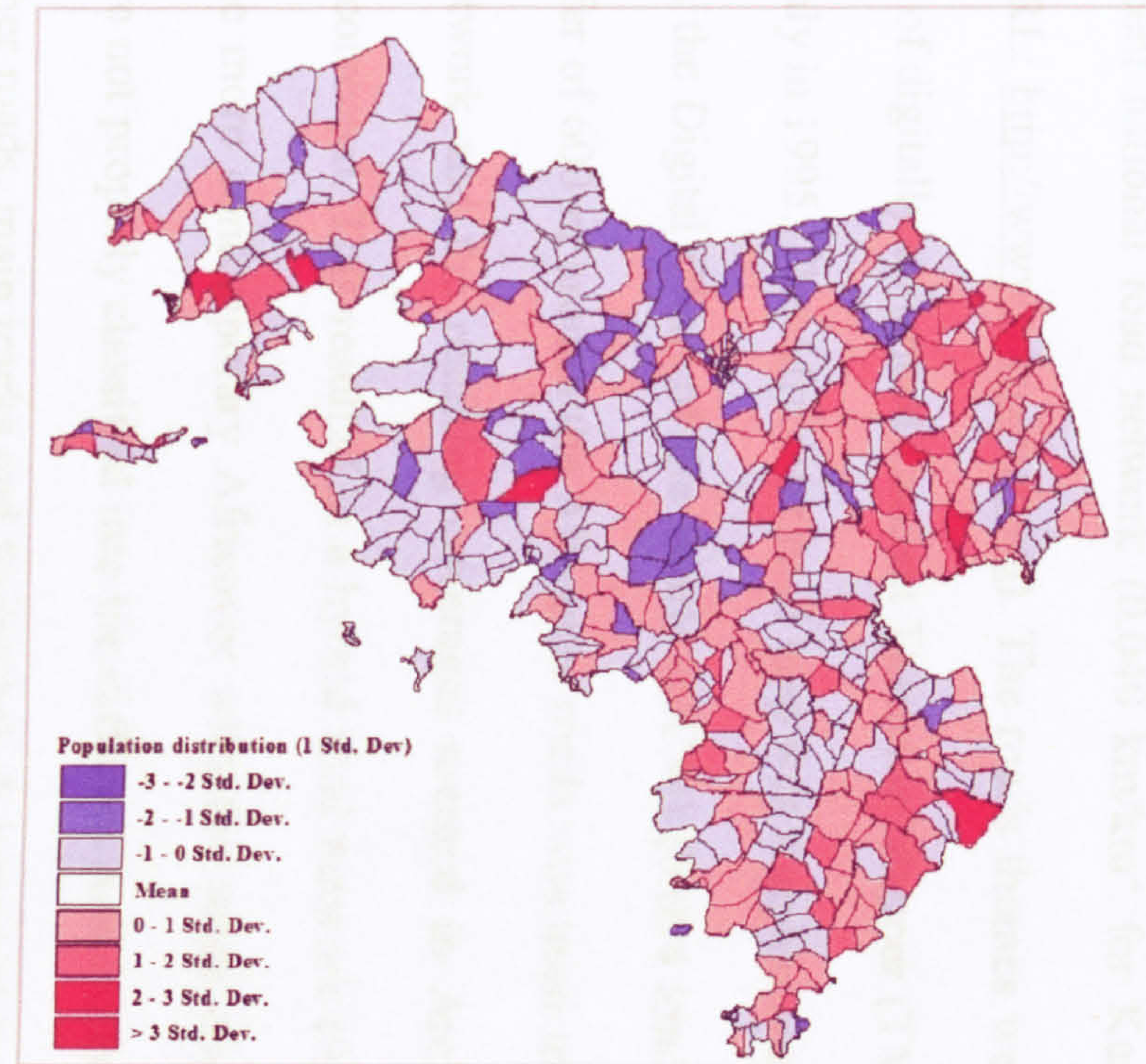
Even though the national population map performs better than any of the existing large scale population databases in Kenya (Hay *et al.,* 2005) it is nonetheless associated with some level of error as depicted by the RMSE values for the test districts and Kappa values of the settlement for the four districts used to develop the model (Table 5.12). The exact nature of this uncertainty and how it propagates through the entire national population distribution map has not yet been quantified but is the subject of an on-going research. In the absence of this, any population denominators based on the national map will contribute to an increased level of uncertainty in the accessibility models developed in Chapter 4.

Figure 5.8 Maps comparing the distribution of population based on the national map to the district specific EA presented as 1 standard deviation from the mean

a) Bondo district map of population distribution on the modelled national population



b) Bondo district map of population distribution based on the EA census data



5.4 Transport network

5.4.1 Developing the national transport network

The most recent national road network (0.040 km/km^2 for Kenya) was obtained from Africover (URL: http://www.africover.org). The roads themes were produced from visual interpretation of digitally enhanced Landsat Thematic Mapper (TM) images (bands 4, 3, 2) acquired mainly in 1995. The Africover road map was supplemented with the road network supplied with the Digital Chart of the World (DCW) (0.094 km/km^2 for Kenya) (Danko, 1992). A buffer of 600 m around the Africover roads was used to erase duplicate roads in the DCW network and the resulting coverages merged in ArcView 3.2 and manually checked and corrected. This resulted in a hybrid road network (0.074 km/km^2 for Kenya) optimising the more contemporary Africover with the more comprehensive DCW. The road data were not properly classified into the different road classes in Kenya (all-weather and dry-weather roads, main tracks and footpaths). A long and painstaking effort has been invested in developing high-resolution and elaborate road network for the four study districts, mainly from EA maps covering primary and secondary roads, railroads, tracks and footpaths (Section 2.4.4). For the four study districts, this national road data were used as the template for roads layer which were then updated and classified from 1:50,000 topographic maps and EA maps.

5.4.2 Result, accuracy and precision

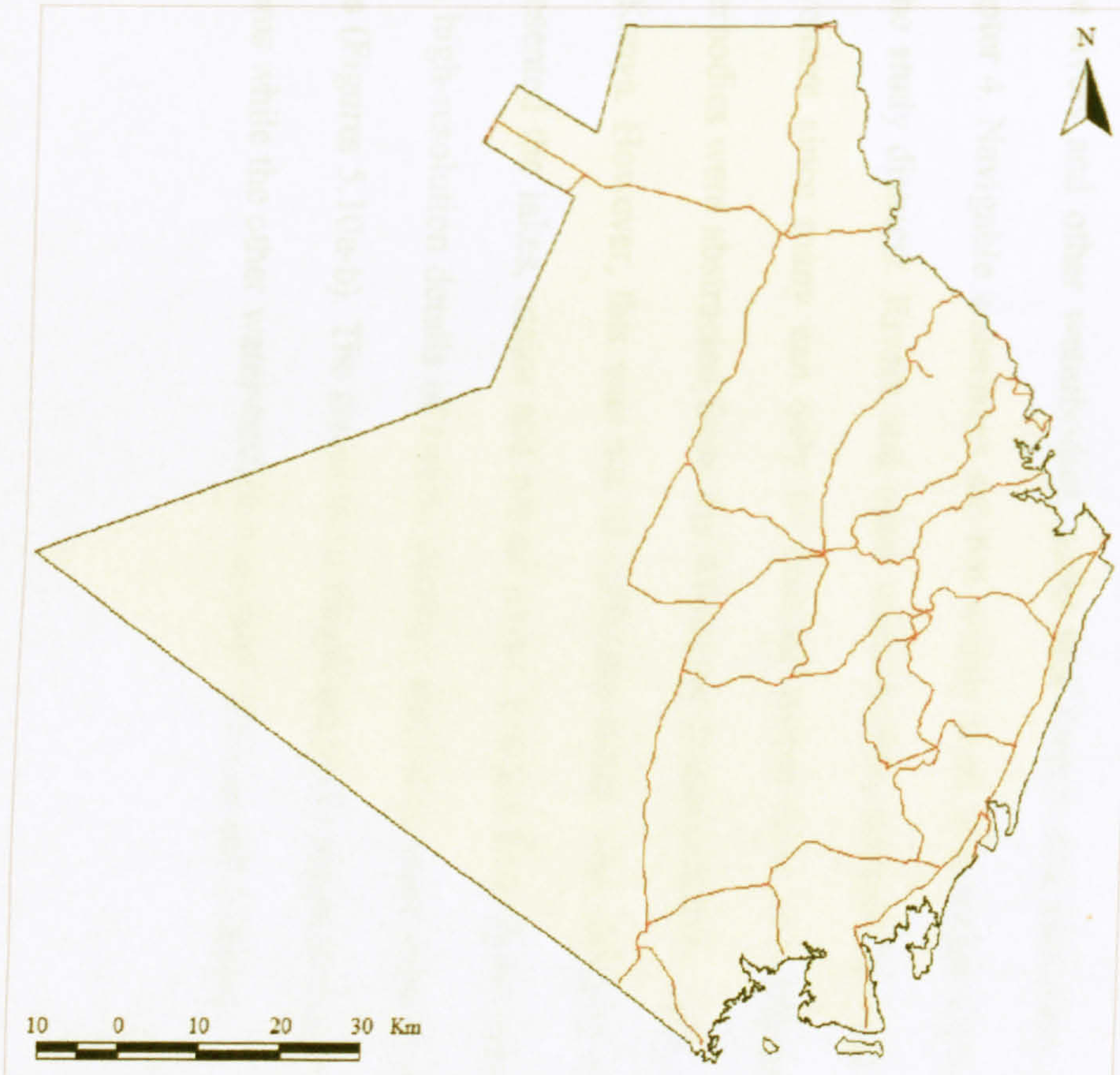
The gap in resolution between the Africover-DCW and the high-resolution study districts' road network is shown by the example of Kwale in Figures 5.9a-b. The difference in the coverage between the two types of road network was almost 2.5 times for Kwale and between 2.2 and 3.3 folds for the other districts. The national road map comprised only primary and secondary roads. The road map developed for the study districts contained tracks, footpaths, primary and secondary roads of even higher resolution and coverage than their national equivalent. There was also a difference in the spatial accuracy of the two types of road networks, even where the coverage was the same (Figure 5.9c). In the section of Kwale, shown in Figure 5.9c, there was a vertical shift > 250 m between similar segments of the national road compared to the district-level road network.

5.4.3 Implications for scaling-up the accessibility model to the national-level

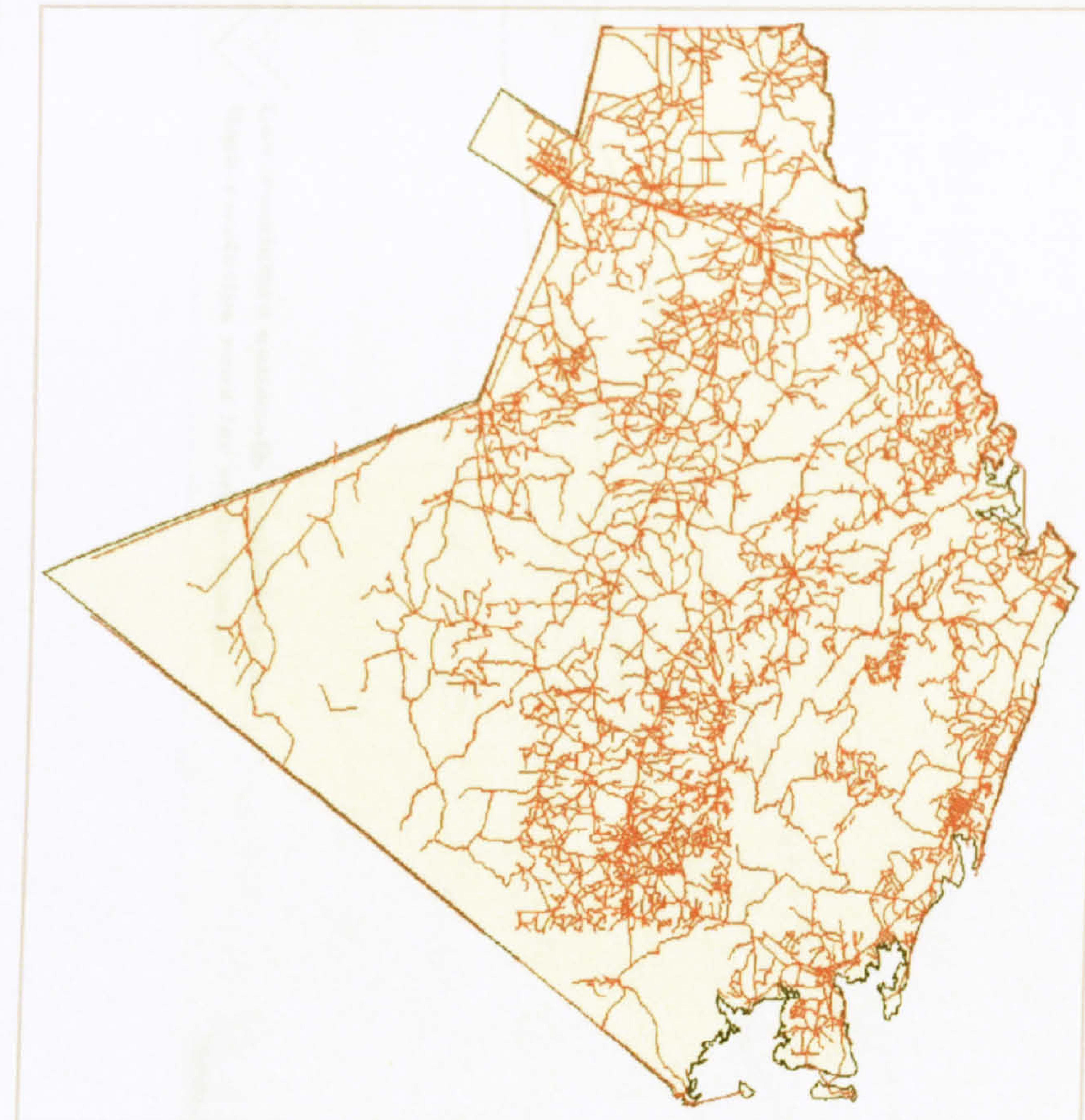
As indicated in Chapter 3 & 4, spatial access to health services is heavily influenced by the presence of accurate and reliable description of the road and other transportation network. In particular, where people mostly walk to health services and models are based on pedestrian movement, the availability of footpaths is crucial. Nationally, the most comprehensive road data available consist only of primary and secondary roads which are at a much lower resolution than those of the study districts. Clearly, the implication of this to the access model is that where road data do not exist, the model algorithm mimics the straight-line model and tends to overestimate access to health services and inaccurate definition of health facility catchment boundaries. Further, where the boundaries are not defined as precisely as will be the case with the use of poor road network, boundary adjustments based on differing facility types may introduce even further uncertainties. Another implication of the low-resolution and poor coverage of the road network is that it was used as an input in modelling the national population distribution described in Section 5.3. As such part of the error in the population map is due the road network.

Figure 5.9 Maps highlighting the difference in coverage of available nationally compared with that developed specially for the study districts: the example of Kwale

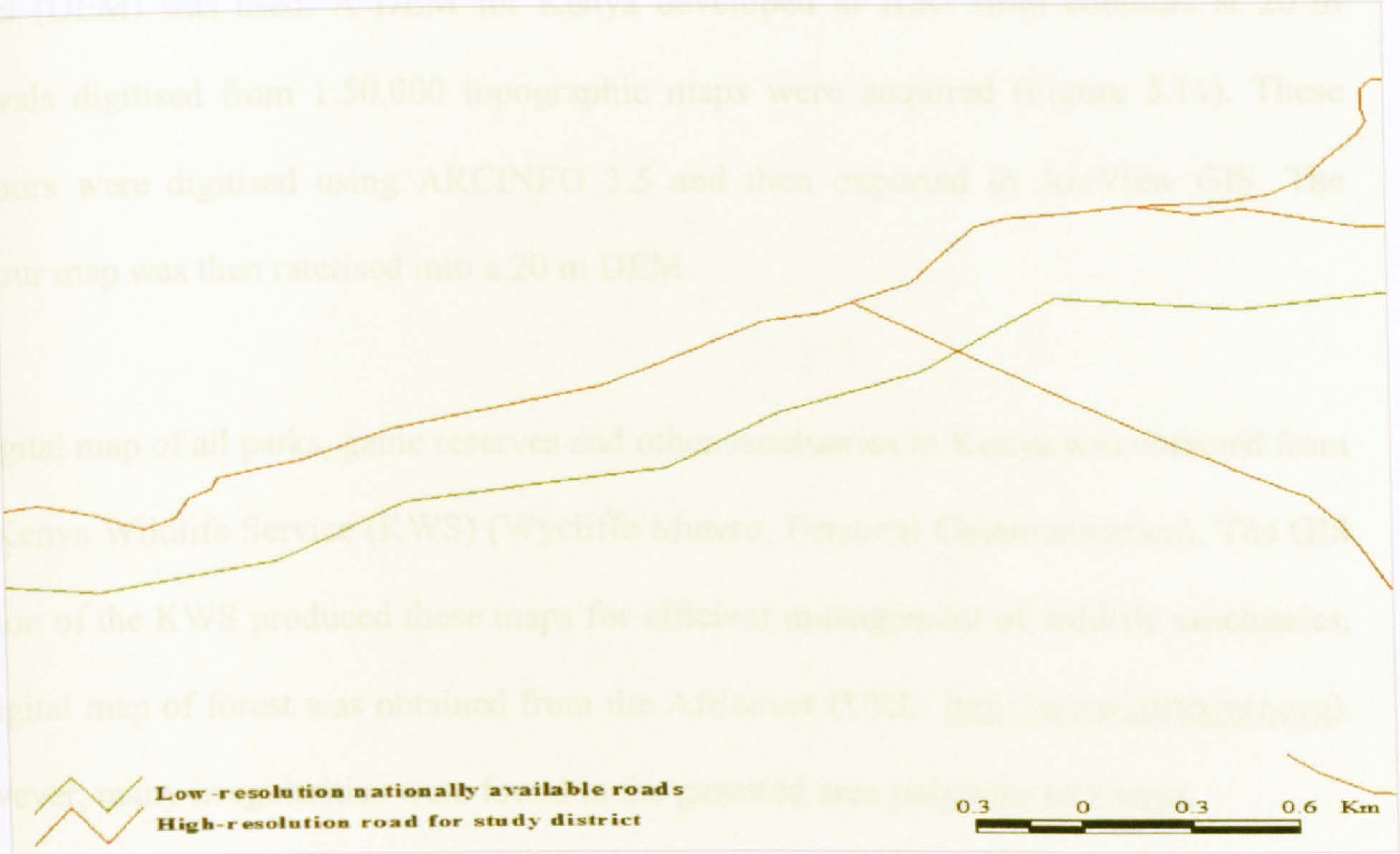
a: Africover-DCW road network



b: District specific road network



c: A section of Kwale showing the difference in resolution between the nationally available road and the high-resolution road developed for the study. In some sections, the difference was > 250 m



5.5 Other national data

5.5.1 Rivers and other waterbodies, gazetted areas and elevation data

In addition to health service and population data, other data required for the access model were rivers and other waterbodies, parks and forests and elevation data as described in Chapter 4. Navigable waterways are not widely used as a means of transportation in most of the study districts. Rivers and other water-bodies, nonetheless, act as obstacles to free movement since many can only be crossed where there is a bridge. Rivers and other waterbodies were abstracted from the Africover database (URL: http://www.africover.org) for Kenya. However, this was not of sufficient detail. The national drainage map mainly represented the lakes, major and minor rivers. For the four study districts EA-level maps with high-resolution details of rivers, swamps and lakes were used to update the Africover maps (Figures 5.10a-b). The rivers were classified into perennial river and seasonal river or streams while the other water-bodies consisted of lakes and swamps.

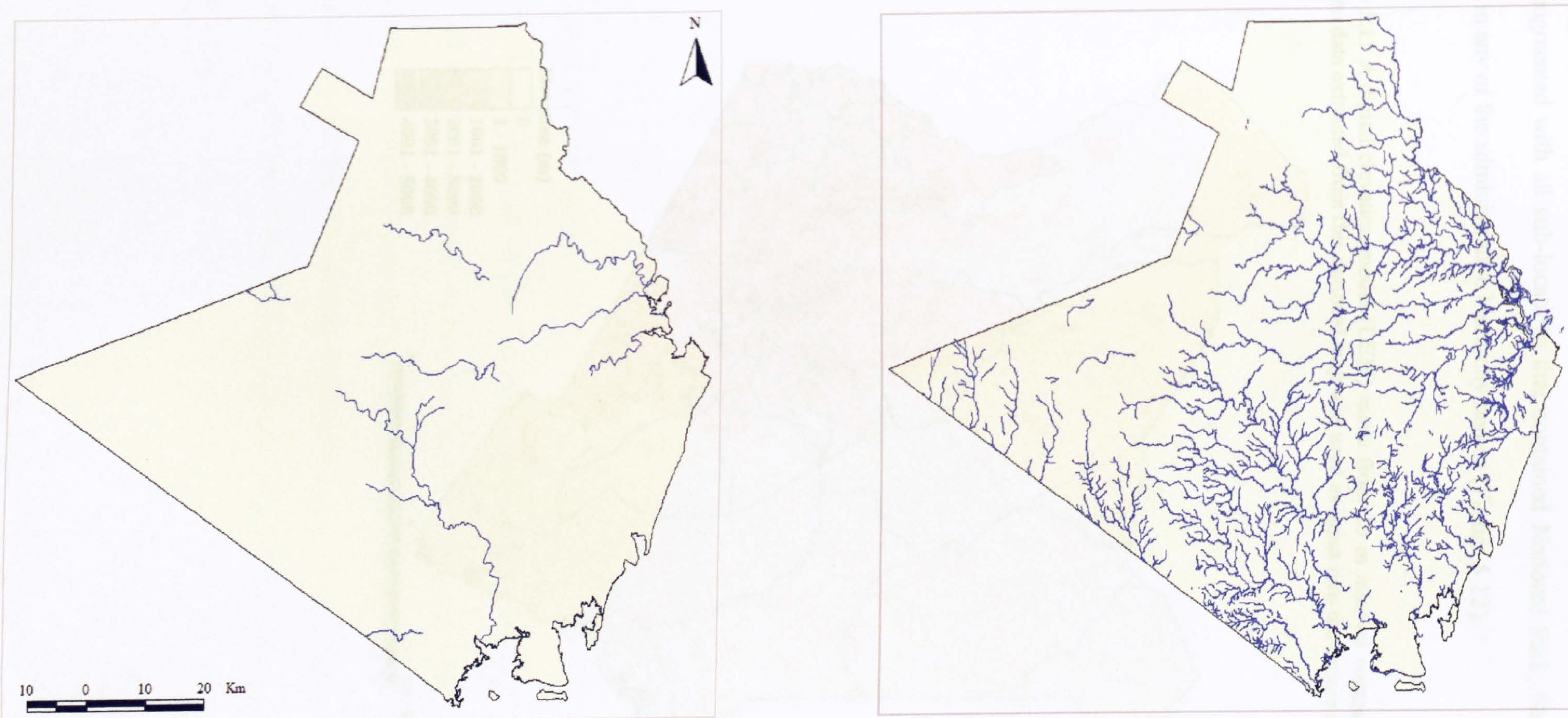
To determine the influence of slope on accessibility to health services, a digital elevation model (DEM) was used. A DEM for Kenya developed at ILRI from contours at 20 m intervals digitised from 1:50,000 topographic maps were acquired (Figure 5.11). These contours were digitised using ARCINFO 3.5 and then exported to ArcView GIS. The contour map was then raterised into a 20 m DEM.

A digital map of all parks, game reserves and other sanctuaries in Kenya was obtained from the Kenya Wildlife Service (KWS) (Wycliffe Mutero, Personal Communication). The GIS section of the KWS produced these maps for efficient management of wildlife sanctuaries. A digital map of forest was obtained from the Africover (URL: http:\\www.africover.org). However, many irregularities were found in the gazetted area polygons of Kenya.

Figure 5.10 Maps of Kwale comparing the coverage of national Africover rivers to those developed specifically for the study districts

a: Africover national rivers map

b: High-resolution rivers map developed for the study districts



The polygons over land were checked against all ancillary data and manually corrected if their boundaries did not reconcile (i.e. if a gazetted area boundary followed an administrative border, road or river boundary inaccurately it was corrected). These polygons were augmented with all sub-locations that contained National Park, National Reserve or Forest in any of the administrative hierarchy names (Figure 5.12).

Figure 5.11 A digital elevation model (DEM) made from 20 m interval contours. District specific elevation data extracted from this national map was used as input into the access models in Chapter 4

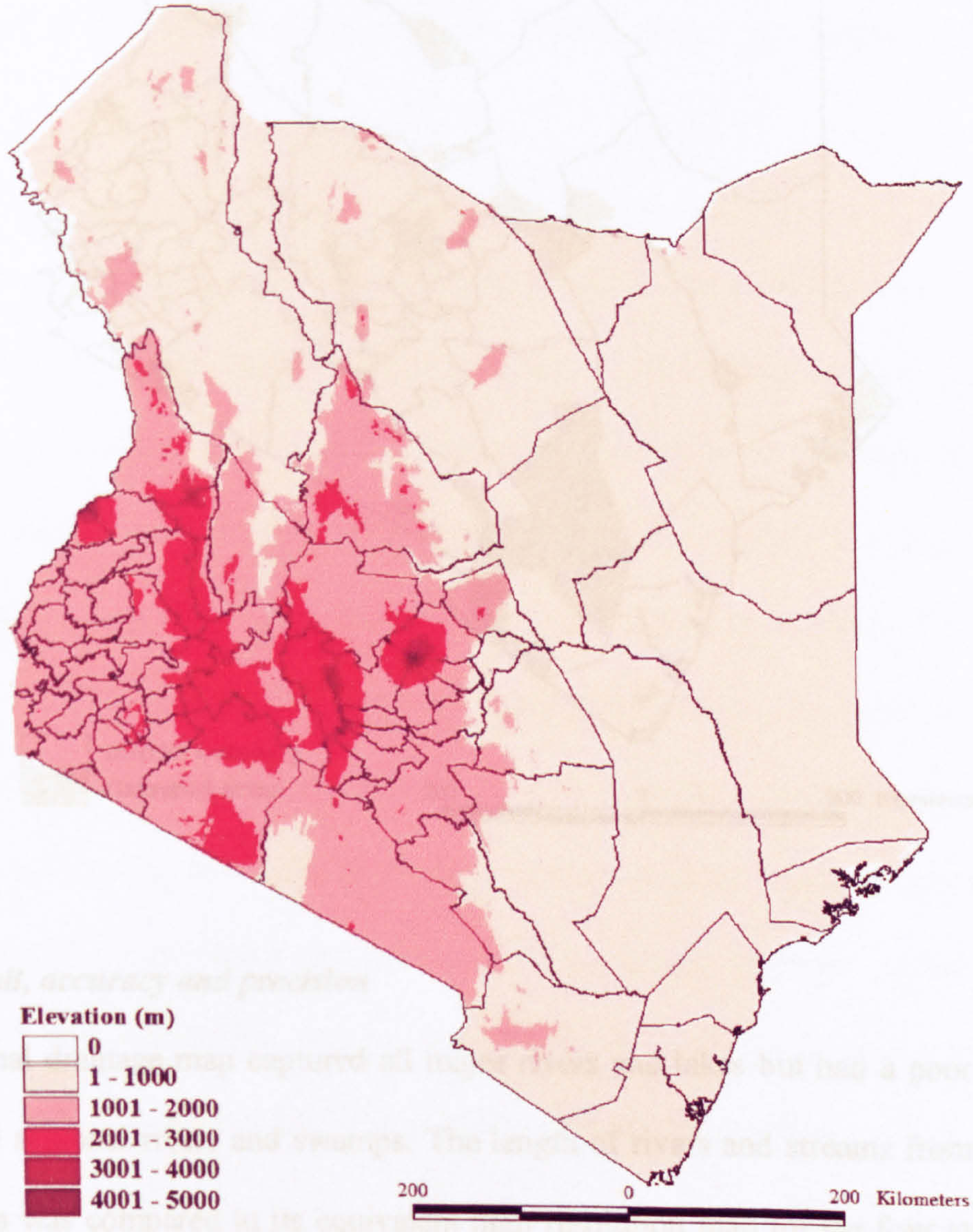
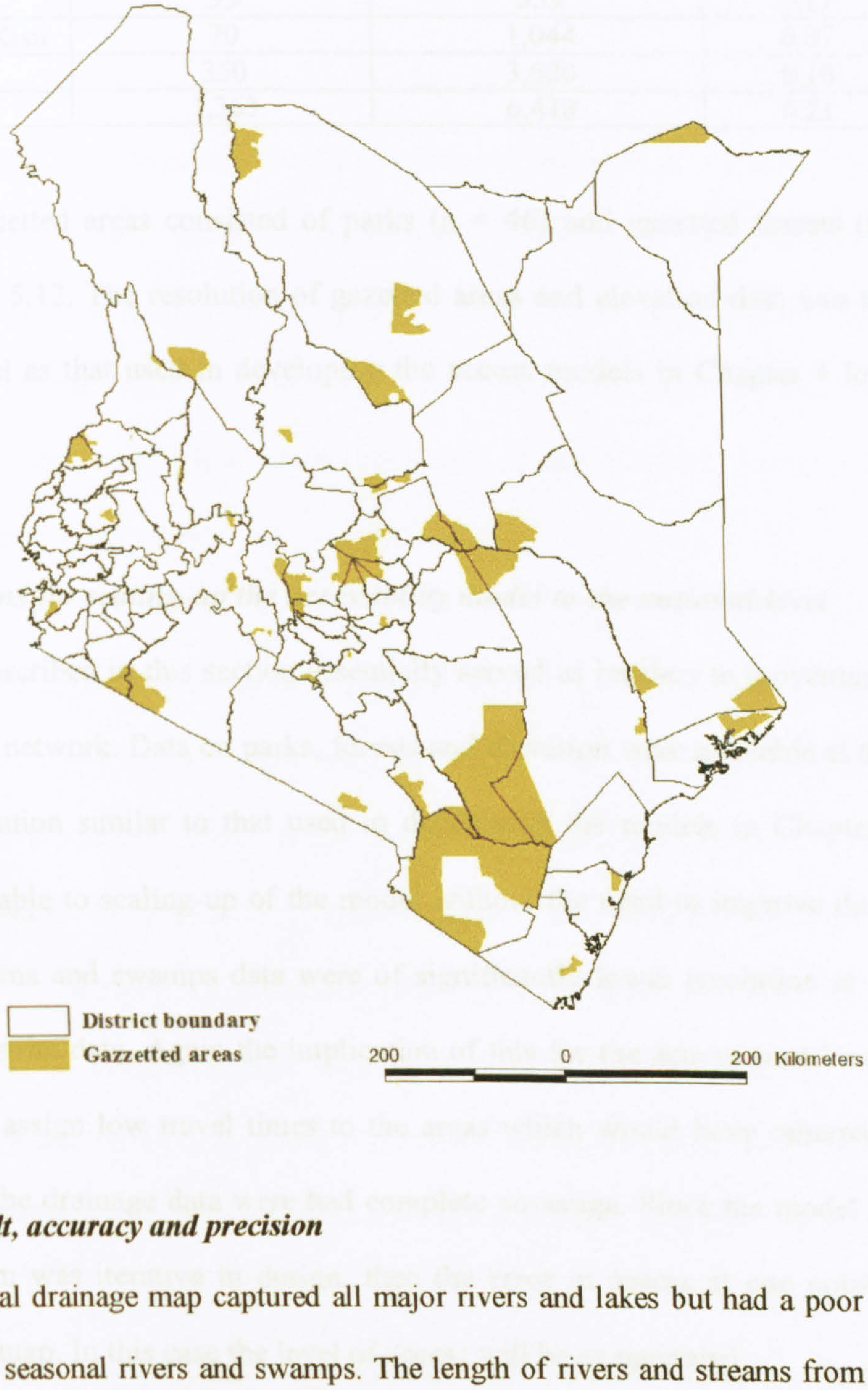


Figure 5.12 A national map of gazetted areas. District specific parks, reserves, sanctuaries and forests data extracted from this national map was used as input into the access models in Chapter 4



5.5.2 Result, accuracy and precision

The national drainage map captured all major rivers and lakes but had a poor coverage of minor and seasonal rivers and swamps. The length of rivers and streams from the national rivers map was compared to its equivalent high resolution map for the four study districts. The result showed that the national rivers map had a poor resolution with coverage of between 7% and 21% of the river network developed specifically for the study districts (Table 5.13).

Table 5.13 Comparison of the coverage of the national rivers map to the district specific rivers map

	Length of national rivers data (km)	Length of district rivers data	Ratio
Bondo	93	559	0.17
Greater Kisii	70	1,044	0.07
Kwale	350	3,620	0.10
Makueni	1,363	6,418	0.21

The national gazetted areas consisted of parks (n = 46) and gazetted forests (n = 20) as shown in Figure 5.12. The resolution of gazetted areas and elevation data was the same at the national-level as that used in developing the access models in Chapter 4 four the four study districts.

5.5.3 Implications for scaling-up the accessibility model to the national-level

The data sets described in this section essentially served as barriers to movement of people on the transport network. Data on parks, forests and elevation were available at the national-level at a resolution similar to that used in developing the models in Chapter 4 and are therefore, amenable to scaling-up of the model without the need to improve the data. Only the rivers, streams and swamps data were of significantly lower resolution at the national compared to district data. Again the implication of this for the access model would be that the model will assign low travel times to the areas which would have otherwise had high travel times if the drainage data were had complete coverage. Since the model JOURNEY-TIME algorithm was iterative in design, then the error in access at one point propagates throughout the map. In this case the level of access will be exaggerated.

5.6 Potential of available national-level data in scaling up the 'best-fit' access model

In the light of the limitations of national data described in the previous sections, an investigation was still needed to determine the potential of the available national-level data in scaling up the models. In Section 5.2.7, it was shown that adjustment of catchment boundaries for actual use of health services would not be possible because of the large error in the health facility coordinates. Model 4 unadjusted, described in Chapter 4, was therefore used for this experiment. First from the national-level low-resolution input data, district-specific data were extracted and used to the run the model. Then the same model was implemented using primary and secondary roads derived from the high-resolution district road map. This was done to assess the performance of the models when roads of the same type but different detail and resolution were used. Finally, predictive accuracy assessment using Kappa statistic and proportion of population within 5 km of GoK-MoH health services were computed for the models. These results were then compared to those of the model using high-resolution input data, including roads at the footpath level, and Model 1 (Euclidean) as described in Chapter 4.

In comparing the models, predictive accuracies of the model based on high-resolution district-level data, referred to henceforth as Model 4a_district, were considered the benchmark. First the model based on low-resolution national data (Model 4_national) was compared to Model 4a_district. The result showed that Model 4_national had poorer predictive accuracy and put a substantially larger proportion of population within 5 km of GoK-MoH health facilities compared to high-resolution Model 4a_district. For the four districts, Model 4_national put between 10-23% percent more people within 5 km of GoK-MoH health services than Model 4a_district with a difference in Kappa value of 0.9 (Table 5.14 and Figure 5.11). Model 4_national was then compared to the model implemented using only the high-resolution primary and secondary roads (Model 4b_district), that is, without the footpaths. The primary and secondary roads extracted from the high-resolution district data were 3-fold more detailed than the equivalent road map extracted from the national road network. The analysis showed that Model 4_national again had a lower Kappa value than Model 4b_district and assigned between 6-9% more people to the 5-km threshold of GoK-MoH health services. Third, Model 4_national was compared to the Euclidean model and was found not to perform better with although with a lower kappa value (Table 5.14 and Figure 5.13).

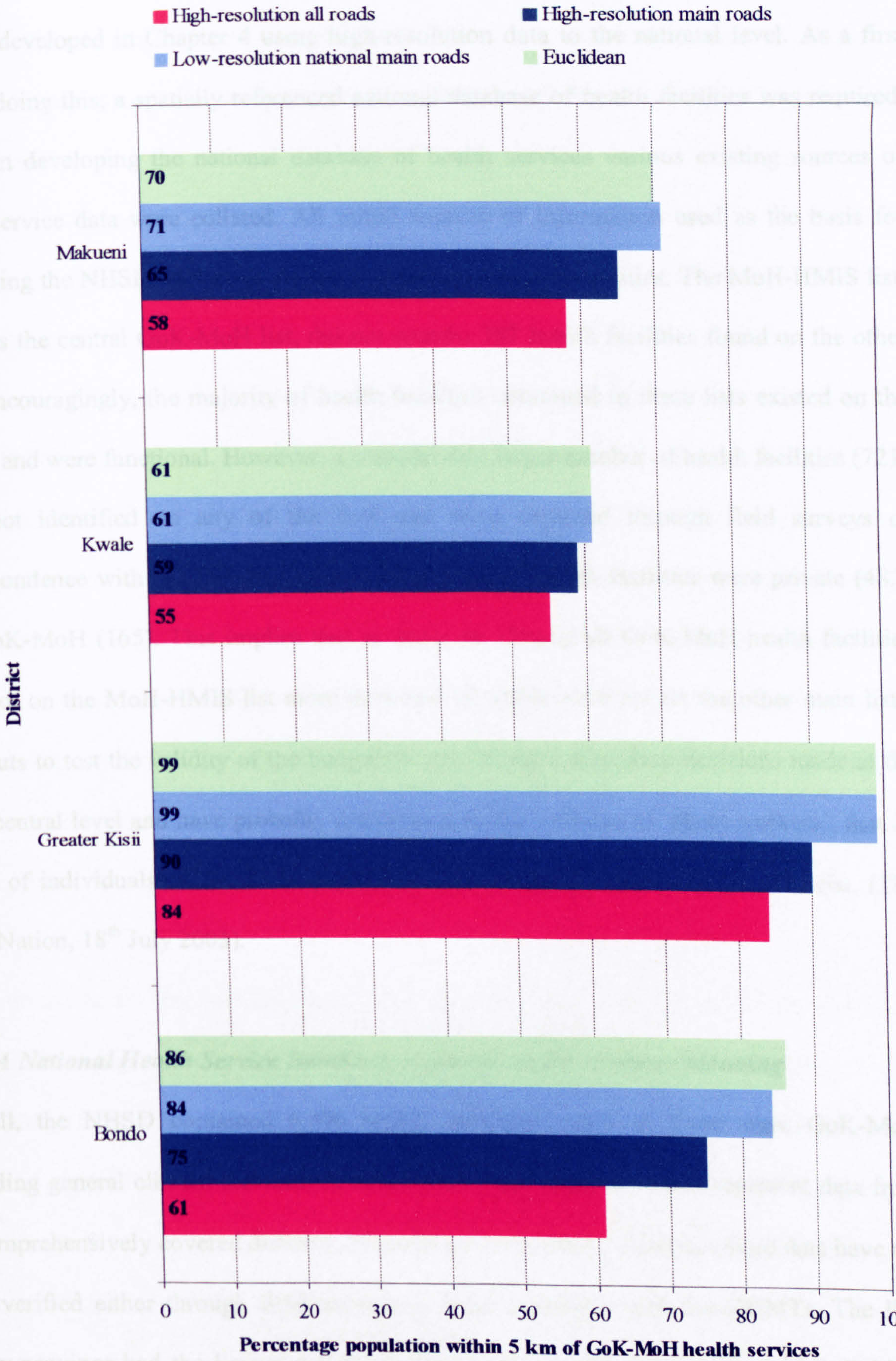
In summary, the model using the available national data had the poorest predictive accuracies and was even worse than Euclidean model (Table 5.14 and Figure 5.11). Model 4b_district, which was based on high-resolution primary and road network, extracted from the road map specifically developed for the study district, had greater precision than Model 1 and Model 4_national.

Table 5.14 Comparison of models performance from high- to low resolution input data

Data input	**Model 1 (unadjusted)** Euclidean (Model 1)		**Mode4a_district (unadjusted)** All roads (high-resolution)		**Model 4b_district (unadjusted)** Primary & secondary roads (high-resolution)		**Model 4_national (unadjusted)** Primary & secondary roads, national (low-resolution)	
	Percent population within 5km	Kappa	Percent population within 5km	Kappa	Percent population within 5km	Kappa	Percent population within 5km	Kappa
Bondo	86	0.71	61	0.74	75	0.71	84	0.65
Greater Kisii	99		84		90		99	
Kwale	61		55		59		61	
Makueni	70		58		65		71	

These findings have major implications on scaling up of the high-resolution detailed district-level models of GoK-MoH health service access to a national scale. Despite best efforts to reconstruct required input data at a national-level, the quality and precision of the attribute data are inadequate to capture the spatial features of health service access. As things stand, the access model developed in Chapter 4 cannot be scaled-up nationwide with any semblance of plausibility.

Figure 5.13 Changes in population's access to GoK-MoH health services for Model 1 (Euclidean) and Model 4 (based on different resolution of road data) to assess varying model performances



5.7 Discussion

The aim of this chapter was to explore the possibility of interpolating the spatial accessibility models developed in Chapter 4 using high-resolution data to the national level. As a first step to doing this, a spatially referenced national database of health facilities was required. To begin developing the national database of health services various existing sources of health service data were collated. All initial sources of information used as the basis for developing the NHSD contained different numbers of health facilities. The MoH-HMIS list, which is the central GoK-MoH list, did not contain 307 health facilities found on the other lists. Encouragingly, the majority of health facilities contained in these lists existed on the ground and were functional. However, a considerably larger number of health facilities (721) were not identified on any of the lists and were captured through field surveys or correspondence with the DHMTs. Most of these 'new' health facilities were private (482) and GoK-MoH (165). This implies that as many as 15% of all GoK-MoH health facilities were not on the MoH-HMIS list more than half of which were not on the other main lists. This puts to test the validity of the budgetary and resource allocation decisions made at the MoH central level and have probably contributed to the problem of 'ghost workers', that is, names of individuals on the MoH payroll of employees who in reality do not exist. (The Daily Nation, 18th July 2003).

5.7.1 A National Health Service Database: implications for resource planning

Overall, the NHSD contained 6,496 health facilities, 2,041 of these were GoK-MoH providing general clinical services, of which 98% were mapped. These represent data from 38 comprehensively covered districts, 19 partly covered and 12 districts whose data have not been verified either through field surveys or correspondence with the DHMTs. The Rift Valley province had the largest and North Eastern the lowest concentration of GoK-MoH health facilities. However, the highest growth rate in health facilities in the period 1959-2004 was in North Eastern (7.2%) and the lowest was in Coast (3.3%) province.

It is evident that a crucial factor in any attempt at equitable health resource planning is accurate information on the nature of the existing health services in terms of the number of health facilities, personnel and other utilities. The location of these services in relation to population, poverty or disease vulnerability underpins efforts to achieve equitable health service reform.

Many studies into the health sector in Kenya, including some commissioned by the Ministry of Health, have reported conflicting numbers of health facilities in the country. A study carried out by Development Solution for Africa, a private commercial company, on behalf of the MoH-DPHC in 1995-96 showed that there were 3,493 health facilities of which 2,120 were GoK-MoH (DSA, 1998). The HMIS morbidity and mortality report for 1996-2000 period indicated that there were 4,294 health facilities, 2,252 of which were GoK-MoH (MoH, 2001). The 2004 Government Sessional Paper No. 2 on National Social Health Insurance in Kenya states that healthcare in the country is delivered through a network of 15,400 health facilities made up of 5,400 primary health care facilities (hospitals, health centres and dispensaries), 60% (3,240) of which are run by the government, and 10,000 private clinics (MoH, 2004b).

The main reason for this confusing and inconsistent reporting is that these figures have been collated from single sources of information and little effort has been made to consult with people at the district level for verification and updating. In addition, the government's weak system of regulating the private health sector has resulted in the proliferation of unregistered health clinics. As such figures from this sector are usually presented as best-guess estimates with unquantified precision. Any budgetary and resource allocation plans and attempts to enhance intersectoral corporation based on these data will undermine the goals of improving health care that have been consistently advocated for in the various national and international strategic reports, especially in a low income country like Kenya with a steadily declining per capita health expenditure. It is astonishing in an environment of such severe resource constraints that the resource allocation decisions are based on such grossly inadequate information. How many and where health services are located must be the fundamental cornerstone of all planning initiatives.

5.7.2 Scaling-up models of health service access to the national-level

In exploring the utility of the NHSD and other databases described in this chapter in modelling spatial accessibility, several key findings crucial to defining such models in Kenya and similar settings have been made. As with most modelling exercises, developing models that are designed to predict complex epidemiological events require the best possible data input to ensure that model outcomes do not vary significantly from the real event. When scaling-up such high-resolution input to the national-level where only lower resolution data are available, it is inevitable that the accuracy of the model will decrease. The critical decision to be made at this stage, therefore, is to determine the level of reduction of model accuracy that is acceptable given the practical problems of developing high resolution data at national scale.

The last analytical section of this chapter was aimed at exploring the readiness of the nationally available data in scaling up the 'best-fit' accessibility model. The key observation from the analysis of the utility of existing data is that scaling-up the model inevitably requires significant improvement of existing national health services, roads and drainage data both in terms of coverage and resolution.

The results of the models for the study districts were used to represent the likely outcome at the national level. If Euclidean model, which is commonly used as measure of health coverage was used, 82% of Kenya's population will be within 5 km of public formal government health services. If the available national data were used, and the model was not adjusted for competition between different facilities, over 81% of the population would be considered to be within the 5-km threshold of GoK-MoH health facilities. Using the next best model (relying on high-resolution primary and secondary roads) the proportion will be 74%. The high-resolution model, when extrapolated from the results for the four districts even when not adjusted for actual use, shows that only 68% of the population are within 5-km of GoK-MoH health services. The difference between currently used estimates of access and the result of the unadjusted high-resolution model was 14%. This implies that, even without adjusting the models for competition between health facilities, over 4 million more people are probably incorrectly estimated to have access to government health services by the current methods of measuring access.

In summary, the spatial accessibility models developed in this thesis have the potential of better defining health inequity driven by geography and can also act as a framework for incorporating socio-economic data relevant to assessing health equity. But at the national level, better high-resolution input data need to be developed to achieve the full potential of this model. Serious investment in a national GIS infrastructure will be required to facilitate such developments.

CHAPTER 6:
Conclusion

Distance to health services is an important variable in access to health care (Section 1.5.3). Access to health care is a major determinant of health, itself a driver and measure of sustainable development. Both the MDGs and the PRSPs have outlined several health development goals and targets in poverty reduction, which are largely dependent on access to effective preventive and curative measures. However, while several studies have shown the importance of distance in determining access to health services, there has not been an equal amount of research into the methods of measuring the distance variable in health studies.

This thesis set out to tackle the methodological issues related to measuring spatial access to GoK-MoH health services in the management of fever in four districts in Kenya. The reason for choosing fever as a tracer of health service access and utilisation was because it contributes more than a third of all morbid events among young children in Kenya and is the major treatment burden at government health facilities. Fever is a predominant feature of malaria and in concert with the MDGs and RBM, and central to the Kenya National Malaria Strategy is the reduction of the malaria burden by improving access to effective preventive and treatment measures for malaria.

The data used in the thesis can be divided into three broad categories;

1. High-resolution GIS data on GoK-MoH health service providers, population, transportation infrastructure, land cover and topography for the four study districts described in Sections 2.4.1-2.4.7

2. A survey of paediatric febrile patients seen at a sample of GoK-MoH health facilities and linked to the village of residence in the four districts described in Section 3.3.2. The data involved 81 health facilities resulting in interviews of 1668 febrile paediatric patients

3. A community household survey on sources of treatment (GoK-MoH and other alternative sources) among children under the age of 5 years who had reported a fever in the last 14 days in the four study districts described in Section 4.2. This involved 1,908 children who sought treatment, of which 668 were treated at GoK-MoH health facilities

Considerable effort has also been put into developing a national map of formal GoK-MoH, mission, NGO and private health services, the first atempt since 1959. Other national data collated for the thesis include data on population distribution, infrastructure, relief and topography at a lower resolution as described in Sections 5.2-5.5. The aim of this was to explore the possibility of developing a national map of access and utilisation of health services.

As shown in Figure 1.5, the methodological process and modelling exercise in this thesis proceeded in several iterative steps. The first analytical approach, described in Chapter 2, was to define theoretical access to the nearest GoK-MoH health facilities in each district using a Thiessen polygon (TP) technique. The simplest definition of proximity, the Euclidean or straight-line distance, was used to define catchment polygons around each GoK-MoH health facility, using enumeration area (EA) level population data. The Euclidean distance is presently used to estimate spatial access by the Kenya government and many UN agencies. The analysis in this chapter showed that there were marked disparities in theoretical Euclidean access between districts and within districts, particularly urban and rural differences. According to these analyses, in both Kwale and Makueni, about 30% or more of the population lived more than 5 km from a GoK-MoH health facility while in Greater Kisii and Bondo these were about 1% and 14% respectively. When all districts were combined, 82% of the population lived within 5 km of GoK-MoH health services.

In Chapter 3, the second iterative step was to test how much actual use from the GoK-MoH health facility survey of paediatric patients related to the predicted use at the EA level. In this chapter, the spatial analysis of formal Government service providers was used to investigate two broad issues; a) determining the role of distance in health service access and use; and b) assessing the method used to define health facility catchments. The differences between theoretical straight-line (Euclidean) distance criteria for potential health service use developed in Chapter 2 and the Euclidean distances travelled by paediatric patients seeking malaria/fever case-management surveyed in the four study districts were investigated. In the second part of the chapter the TP technique assumptions, that people always use the nearest health facility and that use is homogenous within a facility's catchment area were assessed.

There were several key observations made in Chapter 3. Use of government health services for fever management was shown to correlate highly with distance from these services. Utilisation declined with increase in distance and most patients (50-80%) used the nearest GoK-MoH health facility. Of those patients who did not use closest facility, 60-70% used nearest higher-order facility. The location of a catchment boundary between two adjacent facilities tended to shift in favour of the higher-order facility, contrary to the TP assumption that the boundary was shared equally. When the theoretical Euclidean-based catchment boundaries developed in Chapter 2 were adjusted for competition between facilities, the proportion of population within 5 km of GoK-MoH health facilities decreased by 4% when compared to that prior to adjustment. Finally, a 6-km distance was found to be a threshold beyond which the use of GoK-MoH services for the treatment of paediatric fevers diminished.

The limitations revealed by using traditional TP definitions of catchment areas for health services were addressed in the modelling approach described in Chapter 4. Data from the community household survey in the four districts, and the transportation, drainage, land-use and elevation data were used to provide a more comprehensive and higher resolution approach. Four theoretical spatial access models based on all possible definitions of distance provided by the GIS data for each district were developed. In addition to the Euclidean model in Chapter 2, three other models were developed: i) a model based on the transport network; ii) one based on the effect of elevation into the transport network model to account for the possible effects of slope on movement of people; and iii) one based on the effect of drainage and land-use into the network + elevation model.

Empirical information on patients' use of GoK-MoH health services from the community survey were used to derive adjustment factors describing the position of catchment boundaries between adjacent health facilities. The adjustment factors were then used to calibrate the spatial models using an algorithm that re-allocated the catchment boundaries of each of the four theoretical access models. An overall assessment of the adjusted and unadjusted models was carried out to select the best-fit model. Subsequently, the most optimum modelling approach was adopted. The final analysis in Chapter 4 was the development of GoK-MoH utilisation rate (UR) graphs to overcome the assumption that use of health services was constant within the catchment area. In addition, from the UR graphs an access threshold of use of government health services for the treatment of fevers was derived.

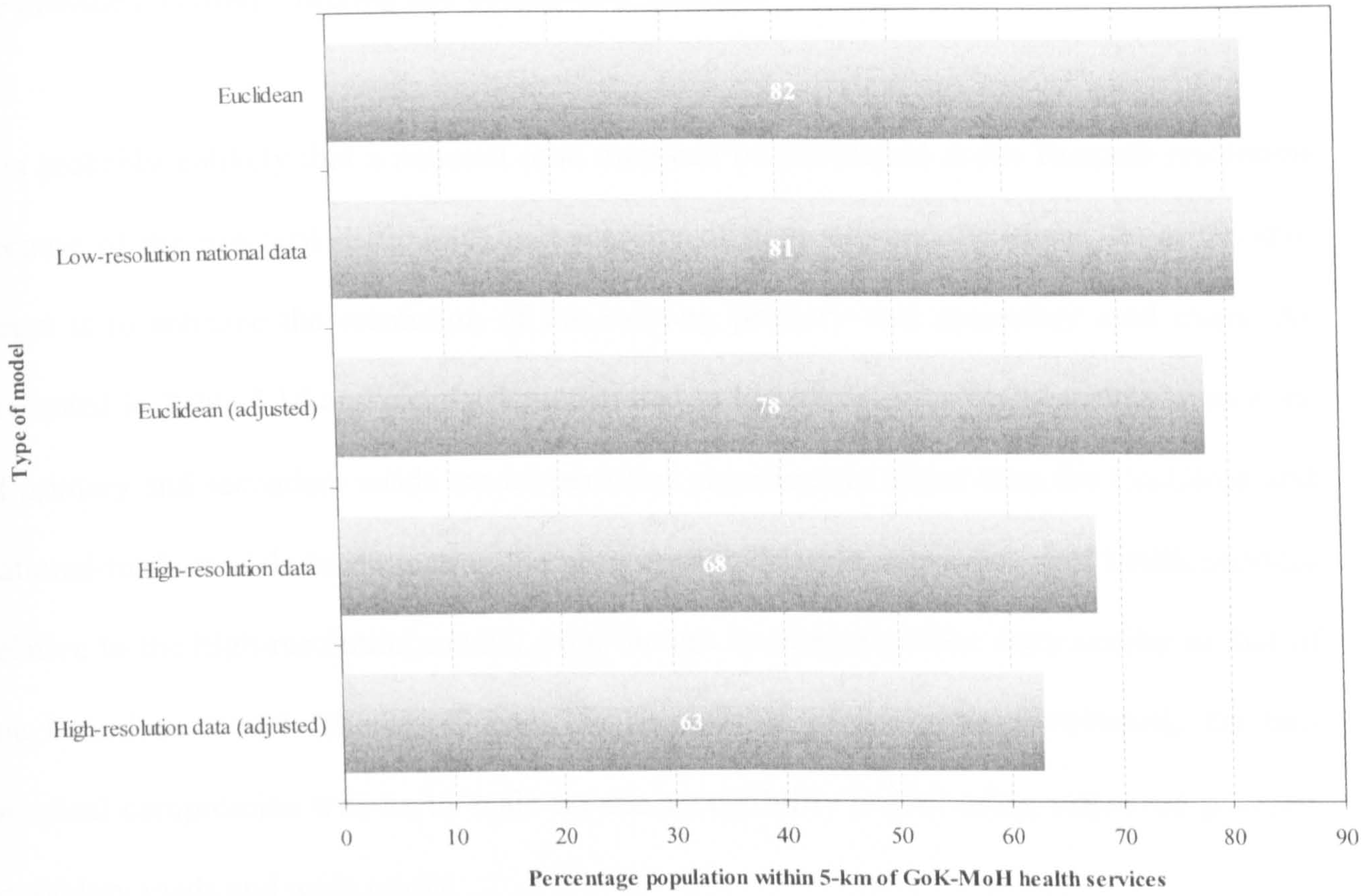
The best-fit model developed in Chapter 4 incorporated data on the transport network, elevation, rivers and other waterbodies and gazetted areas and was adjusted for competition of health facilities of different types. Significant differences were shown between the Euclidean model and those based on the transport network. The best-fit model revealed that 63% of the population in the study districts lived within 5 km of GoK-MoH health services. This was 19% less than the Euclidean model developed in Chapter 2 as shown in Figures 4.18 & 6.1. The current estimates of spatial access to government health services used by the Ministry of Health assigns 19% more people to the 5-km threshold than the best-fit model, which has important implications for the health care access goals in Kenya.

In an effort to scale-up the best-fit model to the national level an attempt was made to reconstruct a national map of health services as described in Chapter 5. The chapter further illustrated how likely a re-constructed health provider and other national databases were to reflect reality and how feasible and accurate their spatial dimension was. The available national data exhibited several important limitations. Overall, appropriate data were either unavailable or existing data were of low precision or poor coverage.

The NHSD probably contained the majority of the GoK-MoH health facilities but it is possible that about 15% of the existing facilities may not be in the database and only 75% of the government health facilities in the database were positioned within 1 km accuracy. An important implication of the low spatial accuracy of the national database of government health services is that any models used at the national level cannot be adjusted for the varying patients drawing of facilities of different types. Although the national population map is better than any of the existing large scale population databases for Kenya, it is nonetheless associated with some level of error whose nature and propagation are yet to be quantified. The high-resolution road network was between 2.2-3.3 times longer than the nationally available one largely due to the presence of footpaths in the former. There also was a difference in the spatial accuracy of the two types of road networks, even where the coverage was the same, in some places almost > 250 m between similar segments. The length of rivers and streams from the national rivers map was between 7% and 21% of the river network developed specifically for the study districts.

When the national data was used in an attempt to scale-up the best-fit access model to the national level, the result for the study districts were significantly different from those of the high resolution data model (Figure 6.1). The model based on the national-level data performed no better than Euclidean model and assigned about 13% and 18% more people to the 5-km threshold than the unadjusted and adjusted high-resolution data models respectively. As such, with currently available national GIS data, its impossible to scale-up the best-fit model to the national level.

Figure 6.1 Comparison of the access model based on available national data to Euclidean and high-resolution data models for the study districts



An extensive amount of empirical work needs to be undertaken to improve existing national health services, road and drainage data both in terms of coverage and resolution. For the health service data, all health facilities, particularly the public ones, need to be enumerated and mapped using GPS. The national road database also has to be updated significantly. The population data error margins need to be established and the associated uncertainties used to quantify the models. For detailed, albeit small-to-medium scale epidemiological work, high-resolution data, including GPS co-ordinates of health facilities and footpath-level road network can be developed. As described in Section 5.2.1, it is possible to significantly improve the health service database using GPS methods. From the present study in four districts the estimate for a two-week GPS level exercise in a medium-sized district in Kenya, including training, transportation and field assistance, costs approximately US$ 5000. Nationally, this would cost US$ 350,000 and is arguably a small price to pay to establish a comprehensive (including private sector) national GIS health service infrastructure. This could be combined with equally important information on what services are provided, staffing, training and commodity gaps etc.

It is probably unlikely that a national road map can be developed at the footpath resolution because of the practical difficulties and scarcity of data sources. However, an achievable target is to enhance the resolution of the existing primary and secondary road maps. As presented in Table 5.14 and clearly demonstrated in Figure 5.13 the high-resolution network of primary and secondary roads model performs significantly better than the Euclidean and national-roads models in estimating the proportion of people within 5 km of health services relative to the high-resolution model, even though its Kappa values were similar to that of the Euclidean model. Therefore, from the perspective of the transport network, the best practical compromise will be to scale up the accessibility model using improved primary, secondary roads and main tracks.

The potential for improving the primary and secondary road network is exemplified by work done at ILRI in 16 districts for the purpose of assessing dairy farmer access to market centres (de Wolf & Staal, 2001). From data for these districts provided to the author by ILRI, the coverage of the road network improved by between 2.7 times relative to the Africover-DCW data. In developing better land-cover and land-use data such as rivers, lakes and swamps, the potential of high-resolution remote sensing satellite data need to be explored (Tatem *et al.*, 2004). Developing all these national databases are beyond the scope of this thesis, and in reality can only be conducted outside the limitations of specific interests of a single research venture, and only within a nationally or multi-sector driven framework.

The best-fit access and utilisation model developed in this thesis overcomes most of the limitations of current accessibility models and is unique in a number of aspects. Often, measures of access to health services are modelled from the supply side such that distances to health services are presented without any information on the number of people at that distance. By using high-resolution population maps, the model has incorporated the demand side of access to health care. The model also overcomes the often-used but erroneous assumption that people always use the nearest health facility by developing a methodology that accounts for the differing patient drawing capacity of adjacent health facilities based on empirical data. A method for defining cross-border use of health services has also been developed through the use of the 95% CI around the discrete boundary between adjacent health facilities. This particular approach of adjusting catchment boundaries for competition between health facilities and the use of 95% CI to define cross-border use is, to the best knowledge of the author, unique to this thesis. The development of utilisation rates, albeit a highly aggregated one, offers a method of describing the heterogeneity of access and utilisation of a health facility within its catchment area, an important aspect ignored by traditional TP techniques. A 6-km kilometre distance has been identified as the threshold beyond which utilisation of government health services for the treatment of fevers diminishes and within which use is steady. This reinforces the use of the 5-km threshold in the national health sector strategy as an appropriate target indicator of spatial access to GoK-MoH health services. Finally, the model does not rely on raw distances to define access to health services, but on travel time, which is a better descriptor of the actual effort required to access health services. On average, a travel time of 1 hour is considered equivalent to 5 km of actual distance.

Despite the best efforts to develop a comprehensive spatial access and utilisation model of government health services for the study districts, the resulting 'best-fit' model has a number of limitations, both conceptual and data related. In hindsight, information on travel time to health services as estimated by those interviewed at health facilities or homesteads should have been obtained during the surveys. This would have enabled the quantification of the travel time as estimated by survey participants to that predicted by the models. Actual travel time for a selected number of health service users in each district should also have been measured to be used in assessing the reliability and accuracy of the models. The absence of this model validation data is acknowledged as a key limitation as it restricts the certainty with which a model performance can be gauged relative to others. In Chapter 3, it would have been more appropriate to use raster based distance measurement methods as was in Chapter 4 rather than the vector based ones which assign EA population to their centroid undermining the resolution of the data. Socio-economic factors, such as income, cost of treatment, cultural beliefs and educational level, have been shown to be very important determinants of access and utilisation of health services (Section 1.5.2). However, the model presented here does not incorporate these factors, largely due to the practical difficulties of obtaining such data at the required household level. An aspect which is included in the model is that of the influence of quality on health services utilisation, but the measure of quality is the statutory MoH designation of service level, which may not reflect the real and/or perceived level of quality at the facility. As such, it becomes difficult to model for the specific characteristics of the individual facility and instead an aggregate measure of quality is used. The selection of at least three more districts: an urban district; densely populated, rich, low malaria risk district from Central province; and a pastoralist district would have made the model more representative of the whole country.

The actual utilisation data used in the modelling approach were derived from a survey of paediatric febrile patients. While the predominant nature of fever presentation at government health facilities might, to some degree, justify its use as a tracer for the broader use of GoK-MoH health services and an indicator of their access by paediatric patients, this may only be satisfactorily representative of infectious diseases. The literature, as described in Section 3.2 shows that the presumptive treatment of fever as malaria enables the treatment of almost all true malaria as such, but results in a high over-diagnosis such that fevers attributable other acute infections are also treated first as malaria. While this leads to the improper use of a considerable amount of anti-malarials, it also serves to strengthen the argument that fever is a good indicator of infectious disease. The exception is TB and HIV/AIDS which currently is predominantly an adult disease and are therefore not sufficiently well captured by the febrile paediatric data used in this thesis. The actual pattern of use of health services for non-infectious diseases, such as cancer, might be significantly different. Nonetheless, it is widely acknowledged that the predominant contributors to the burden of ill-health among children in Kenya are the infectious diseases and are, therefore, the ones that require the greatest amount of planning and resources to reduce child and infant mortality.

The model represents access and utilisation of GoK-MoH health services only and the various other alternative sources of fever management have not been considered fully in the model. In many African settings, as with the study districts, the possible sources of treatment are formal health facilities (GoK-MoH, Mission/NGO and private), retail outlets (pharmacies and shops), traditional healers (herbalists and spiritualists) and self medication. In Kenya, Snow *et al.* (1992) showed that in a survey of mothers in a community around a district hospital on the Kenyan coast, 72% revealed that the preferred choice of treatment for childhood febrile illnesses was with proprietary drugs bought over the counter at shops or kiosks. Similar findings were by reported by Mwenesi *et al.* (1995) and Molyneux *et al.* (1999). Therefore, it is imperative to include into the model the effect of these alternative sources of treatment.

One approach will require that a discrete catchment area, similar to that of the GoK-MoH health services, be developed for these alternative sources. The problem with this conceptual approach is that developing catchment areas around shops or location of traditional healers and other informal sources, such that they are treated as direct competitors of government health services is problematic. While they draw users away form government health facilities, they are not in themselves purely health service providers and their influence is only limited to conditions treatable with over-the-counter drugs and catchment boundaries will only be useful for the specific conditions for which drugs are sold. The formal mission/NGO and private health facilities can be regarded as direct competitors of GoK-MoH health services. However, modelling discrete catchments for them requires sufficient information on patients who use these services. The community survey contained information on only 278 patients who used mission/NGO or private formal health facilities compared to the 668 who used GoK-MoH services, despite the fact that for the study districts, there are twice as many mission/NGO and private formal health facilities as there are government facilities. Another approach to incorporate the use of alternative sources of health services, which has been partially explored in this thesis, was the use of utilisation rate of GoK-MoH health services. The rate of use at any given point within a government health facility's catchment was derived as the proportion of patients who were treated at the health facility at that point, divided by the total number of febrile patients at the same point. However, this could not be incorporated into the wider model since satisfactory utilisation rate could not be developed at the individual facility level because of scarcity of data points. Instead, the main aim of the utilisation rate curve was to demonstrate the variation in use within a catchment area. Nonetheless, fuller appreciation of spatial access to services for the management of paediatric fevers that are more informative to resource planners can only be comprehensively captured by incorporating the mission, NGO and private health care providers. Larger surveys which include the use of these services, not just the prevalence but also the magnitude of use need to be captured.

In defining distance, only pedestrian travel times were modelled, since results from the community survey showed that > 80% of the patients did not incur transport costs to health services and this was considered to be an indication that most people in the districts walked to health facilities, considering the low ownership of private vehicles. Modelling for vehicular speeds for the few who used mechanised transport required information on the type of vehicles, travel schedule, speed etc, which was beyond the scope of this study and unavailable in the public domain. Whilst roads used in the analysis were classified by type and statutory speed limitations, using these to define real-time vehicular speed, particularly where traffic is not regulated, is likely to overestimate the time required to move from one point to the next considering the iterative nature of the distance algorithm. In addition the statutory speed limitations assume optimum road condition, yet the existing road infrastructure in the country is severely damaged. Even for the pedestrian travel times, the rest-time during the journey (due to fatigue) was not modelled as this required information on the length of rest time, which was unavailable to the author and beyond the scope of the study. Nonetheless, a comprehensive definition of distance would have been achievable only if vehicular transport information and rest-time were incorporated into the model.

Information on land-use, such as farming and settlement infrastructure, would have improved the definition of distance as they represent areas where mobility is impossible or restricted, similar to the gazetted areas. However, obtaining such information at the required high-resolution was not possible. Despite the aforementioned limitations, the model has been designed such that it is dynamic and any new data can be incorporated directly into the process.

The spatial government health service access and utilisation model developed in this thesis has a great potential for research, not only for the express purpose of defining spatial access to health services, but also in exploring its relationship with disease burden and poverty. For instance, international comparisons suggest that the average per capita GDP of countries with "intensive" malaria is 5 times lower than that of those without malaria. However, such a correlation may not be sufficient to make the claim that malaria causes poverty, nor whether such a relationship would be true at a sub-national resolution. Using this spatial accessibility model, methods to explore the spatial relationships between malaria risk and access to health services against household resolution poverty data will be explored as an area of immediate research interest. This model could be used in assessing spatial access to water services, schools and markets for farm produce and contribute to the assessment of MDG goals on education, water and sanitation and trade.

The current estimates of access to government health services in Kenya put 19% more people to have access to health services than best-fit model. Therefore, if the outcome of the best-fit model for the study districts was taken to represent the level of national access to government health services, about 6 million people who are thought to have access to GoK-MoH health services within 5 km will actually be outside this threshold. A worrying implication of this is that international and national agencies may be basing their development strategies on levels of spatial access to health care which are much higher than the reality on the ground. Considering the centrality of health in poverty reduction, measurement of the MDG health goals based on current estimates of access in Kenya, and probably in most SSA, will be incorrect. Compounding this problem is the fact that access to other services relevant to MDGs, such as water resources, is also defined using similar inappropriate methods. To redress the situation, more research needs to be done in defining spatial access better by including all the key spatial and aspatial parameters. Ultimately, the use of the best access model at the national level requires the development of more and higher-resolution spatial and empirical data. However, in the light of the cost of such data, a compromise between the high-resolution spatial access model and the commonly used Euclidean model can probably be achieved, first, by profiling all districts based on which of the sampled districts they most relate to in terms of geography, demography, economy and infrastructure. Then, the Euclidean model is then implemented for these districts and the percentage district specific difference between the Euclidean and the high-resolution model based on the profiling is applied to attenuate the results of the Euclidean model. For example, in Makueni, the difference in terms of the population within 5-km of government health services between the Euclidean and the high-resolution model is 7%. If the result of the Euclidean model for a similar district, e.g. Kitui was 65%, then this could be reduced to 58% (i.e. 65-7). However, the sampled districts are not entirely representative of the whole country and additional districts should be selected for study as discussed earlier. To strengthen this approach, the HMIS system in this country needs to fully implemented and improved by gathering additional information on the time patients take to health services, the waiting time for and type of treatment, the length of consultation, gender of patients and greater detail on age structure and diagnosis. Other approaches that can be adopted as an alternative to GIS systems include surveys of actual and perceived travel time to health services by users based on appropriate samples. Surveys of actual travel time will require measurement of user's unprompted journey to health services which are logistically difficult to achieve with an adequately sample. Traditionally, users self-reported estimates of travel time to health services have been used to as a proxy. However, the precision of this estimates are difficult to verify while the end result cannot be used to profile access at the sub-district level.

The spatial access model developed in this thesis has a number of implications with respect to monitoring and evaluation of national health goals. The result of the high-resolution model shows that the health reform target of having everyone within 5-km of health services by 2015 will probably not be achieved. The MDG target of reducing child mortality by two-thirds by providing effective interventions is unlikely to be achieved from the perspective of spatial access and in the light of the most recent data which shows increasing child mortality as described in Chapter 2. Measures of spatial access to services to water and schools which are required to evaluate MDG goals 2 and 7 may also have to be reviewed considering the differences between the Euclidean and high-resolution spatial data models based on the transport network.

Finally, several research questions arise form this thesis that require future attention. Firstly, there is need to develop methods and data to conclusively quantify the reliability and accuracies of the spatial access models. The thesis looks exclusively at spatial access to government health services. As such, appropriate data and methods need to be developed to incorporate the array of competing health sectors, particularly the huge private health service providers. In addition, socio-economic determinants of access need to be incorporated so that a comprehensive view access to health care is adopted rather the limited spatial dimension. Further, districts also need to be identified to increase the national representation in the sample. The cross-cutting applications of these models, particularly in the area of access to services such as water and education also need to be explored. The output of the improved models should be presented in a way that is useful in planning and decision-making.

REFERENCES

Acton, J.P. (1975). Non-monetary factors in the demand for medical services. *Journal of Political Economy,* **53**: 595.

Aday, L.A., Begley, C.E., Lairson, D.R., Slater, C.H. (1998). *Evaluating the health care system: effectiveness, efficiency and equity.* Health Administration Press, Chicago. Pages 334.

Aday, L.U. & Andersen, R. (1975). *Development of Indices of Access to Medical Care.* Health Administration Press, Ann Arbor, MI.

Agha, S. (2000). The determinants of infant mortality in Pakistan. *Social Science & Medicine,* **51**: 199-208.

Airey, T. (1989) The impact of road construction on hospital in-patient catchments in the Meru District of Kenya. *Social Science & Medicine,* **29**: 95-106.

Airey, T. (1992). The impact of road construction on the spatial characteristics of hospital utilization in the Meru district of Kenya. *Social Science & Medicine,* **34**: 1135-1146.

Aitken, R. (1977). *Wilderness areas in Scotland.* PhD Thesis, Aberdeen University, Scotland.

Akin, J.S. & Hutchinson, P. (1999). Health-care facility choice and the phenomena of by-passing. *Health Policy & Planning,* **14**: 135-151.

Akpede, G.O., Abiodun, P.O., & Sykes, R.M. (1992). Relative contribution of bacteraemia and malaria to acute fever without localizing signs on infection in under-five children. *Journal of Tropical Pediatrics,* **38**: 295-298.

Aldana, J., Piechulek, H., Al-Sabir, A. (2001). Client satisfaction and quality of health care in rural Bangladesh. *Bulletin of the World Health Organization,* **79**: 512-517.

Amin, A.A., Marsh, V., Noor, A.M., Ochola, S.A., Snow, R.W. (2003). The use of formal and informal curative services in the management of paediatric fever in four districts in Kenya. *Tropical Medicine & International Health,* **8**: 1143-1152.

Amin, A.A., Hughes, D.A., Marsh, V.M., Abuya, T.O., Kokwaro, G.O., Winstanley, P.A., Ochola, S.A., Snow, R.W. (2004). The difference between effectiveness and efficacy of antimalarial drugs in Kenya. *Tropical Medicine & International Health,* **9**: 967-974.

Amooti-Kaguna, B. & Nuwaha, F. (2000). Factors influencing choice of delivery sites in Rakai district of Uganda. *Social Science & Medicine,* **50**: 2033.

Andes, N. & Davis, J.E. (1995). Linking public health data using geographic information system techniques: Alaskan community characteristics and infant mortality. *Statistics in Medicine,* **14**: 481-490.

Atting, I.A. & Egwu, I.N. (1991). Indicators of accessibility to primary health care coverage in rural Odukpani, Nigeria. *Asia-Pacific Journal of Public Health,* **5**: 211-216.

Bailey, W. & Phillips, D. R. (1990). Spatial patterns of use of health services in the Kingston metropolitan area, Jamaica. *Social science & Medicine,* **30**: 1-12.

Becher, H., Muller, O., Jahn, A., Gbangou, A., Kynast-Wolf, G., Kouyate, B. (2004). Risk factors of infant and children mortality in rural Burkina Faso. *Bulletin of the World Health Organization*, **82**: 265-273.

Bertuglia, C.S., Clarke, M., Forte, P., Claydon, D. (1994). *Models and performance indicators in urban planning: the new policy context.* Modelling the City, Routledge.

Bhatia, J. & Cleland, J. (2001). Health-care seeking and expenditure incurred by young Indian mothers in the public and private sectors. *Health Policy & Planning,* **16**: 55-61.

Birkin, M., Clarke, G., Clarke, M., Wilson, A. (1996). *Intelligent GIS: location decision and strategic planning.* Pearson Professional Ltd., Glasgow.

Black, M., Ebener, S., Aguilar, P.N., Vidaurre, M., El Morjani, Z. (2004). *Using GIS to measure physical accessibility to health care.* World Health Organization, Pan-American Health Organization and RMIT University. Unpublished.

Black, R., Morris, S., Bryce, J. (2003). Where and why are 10 million children dying every year? *Lancet,* **361**: 2226-2234.

Boelaert, M., Arbyn, M., Van der Stuyft, P. (1998). Geographical Information Systems (GIS), gimmick or tool for health district management. *Tropical Medicine & International Health,* **3**: 163-165.

Boller, C., Wyss, K., Mtasiwa, D., Tanner, M. (2003). Quality and comparison of antenatal care in public and private providers in the united Republic of Tanzania. *Bulletin of the World Health Organization,* **81**: 116-122.

Booman, M., Dave, N.D., La Grange, K., Martin, C., Mabuza, F.M., Zitha, A., Fraser, C. Sharp, B.L. (2000). Using geographic information systems to plan a malaria control programme in South Africa. *Bulletin of World Health Organization,* **78**: 1438-1444.

Boulos, M.N.K. (2004). Towards evidence-based, GIS-driven national spatial health information infrastructure and surveillance services in the United Kingdom. *International Journal of Health Geographics*, **3**:1.

Brooker, S., Rowlands, M., Haller, L., Savioli, L., Bundy, D.A.P. (2000). Towards an atlas of human helminth infection in sub-Saharan Africa: The use of geographic information systems. *Parasitology Today,* **16**: 303-307.

Bryce, J., el Arifeen, S., Pariyo, G., Lanata, C., Gwatkin, D., Habicht, J.-P., Multi-Country Evaluation of IMCI Study Group (2003). Reducing child mortality: can public health deliver? *Lancet*, **362**: 159-164.

Bullen, N., Moon, G., Jones, K. (1996). Defining localities for health planning: a GIS approach. *Social Science & Medicine*, **42**: 801-816.

Buor, D. (2003). Analysing the primacy of distance in the utilization of health services in the Ahafo-Ano South district, Ghana. *International Journal of health Planning & Management*, **18**: 293-311.

Burrough, P.A. (1986). *Principles of Geographical Information Systems for Land Resources Assessment.* Oxford Univesity Press, Oxford. Pages 194.

Burrough, P.A. & McDonnell, R.A. (2000). *Principles of Geographical Information Systems.* Spatial Information Systems and Geostatitics, Oxford Univesity Press, Oxford. Pages 333.

Butler, R.J. (1959). Atlas of Kenya: *A comprehensive series of new and authenticated maps prepared from the national survey and other government sources with gazetteer and notes on pronunciation and spelling.* The Survey of Kenya, Nairobi, Kenya.

Byrt, T., Bishop, J., Carlin, J.B. (1993) Bias, prevalence and kappa. *Journal of Clinical Epidemiology*, **46**: 423–429.

Campbell, N.C., Elliot, A.M., Sharp, L., Ritchie, L.D., Cassidy, J., Little, J. (2000). Rural factors and survival from cancer: analysis of Scottish cancer registrations. *British Journal of Cancer,* **82**: 1863-1866.

Canada Cancer Society (2003). *Breaking down the barriers: a study of cancer patient and caregiver needs in Ontario.* Cancer Care Ontario, http://www.canadacare.on.ca.

Central Bureau of Statistics (1994). *Welfare Monitoring Survey II. Basic Report.* Office of the Vice-President and Ministry of Planning and National Development, GoK, Nairobi.

Central Bureau of Statistics (2000). *Poverty in Kenya: incidence and depth of poverty.* Ministry of Finance and Planning, Government of Kenya. Volume 1, pages 89.

Central Bureau of Statistics (2001a). *1999 population and housing census: counting our people for development. Volume I: Population distribution by administrative areas and urban centres.* Central Bureau of Statistics, Ministry of Finance & Planning, GoK, January, 2001.

Central Bureau of Statistics (2001b). *1999 population and housing census: counting our people for development. Volume II: Socio-economic profile of the population.* Central Bureau of Statistics, Ministry of Finance & Planning, GoK, January, 2001.

Central Bureau of Statistics (2003). *Kenya Demographic and Health Survey: Preliminary Report.* Ministry of Planning and National Development, Government of Kenya.

Cicchetti, D.V. & Feinstein, A.R. (1990) High agreement but low kappa. II. Resolving the paradoxes. *Journal of Clinical Epidemiology*, **43**: 551–558.

Chaiken, M.S. (1998). Primary health care initiatives in colonial Kenya. *World Development,* **26**: 1701-1717.

Ciocco, A. & Altman, I. (1954). *Medical service areas and distance travelled for physician care in Western Pennsylvania.* US Public Health Service, Public Health Monograph, No. 19.

Claeson, M., Gillespie, D., Mshinda, H., Troedsson, H., Victoria, C.G. (2003). Knowledge into action for child survival. *Lancet,* **362**: 323-327.

Cleland, J.G. & van Ginneken, J.K. (1988). Maternal education and child survival in developing countries: search for pathways of influence. *Social Science & Medicine*, **27**: 1357-1368.

Cohen, J.A. (1960) A coefficient of agreement for nominal scales. *Educational & Psychological Measurement*, **20**: 37– 46.

Cohen, D.W. & Odhiambo, E.S.A. (1989). *Siaya. The Historical anthropology of African Landscape*. Heinneman, Kenya. Pages 152.

Congalton, R.G. & Green, K. (1999). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Lewis Publishers, New York. Pages 137.

Connor, R.A., Hillson, S.D., Krawelski, J.E. (1995). Competition, professional synergism, and the geographic distribution of rural physicians. *Medical Care,* **33:** 1067–1078.

Coppock, J. T., & Rhind, D. W. (1991). *The History of GIS*. In Maguire, D. J. Goodchild, M. F., & Rhind, D. W., (eds.) Geographical Information Systems: Principles and Applications, London: Longmans Publishers, 1, 21-43.

Cowen, D.J. (1988). GIS versus CAD versus DBMS: what are the differences? *Photogrammetric Engineering and Remote Sensing*, **54**: 1551-1554.

Cox, J., Craig, M.H., Le Sueur, D., Sharp, B. (1999). *MARA/HIMAL technical report 1999: Mapping malaria risk in the highlands of Africa.* London School of Hygiene and Tropical Medicine, UK and Medical Research Council, Durban South Africa.

Craig, M.H., Snow, R.W., Le Sueur, D. (1999). A climate based distribution model of malaria transmission in sub-saharan Africa. *Parasitology Today*, **15**: 105-111.

Creese, A. (1998). In defence and pursuit of equity: a response. *Social Science & Medicine*, **47**: 1897-1898.

Daniels, N., Bryant, J., Castano, R., Dantes, O., Khan, K., Pannarunothai, S. (2000). Benchmarks of fairness for health care reform: a policy tool for developing countries. *Bulletin of the World Health Organization,* **78**: 740–50.

Danko D.M. (1992). The Digital Chart of the World Project. *Photogrammetric Engineering & Remote Sensing*, **58**: 1125-1128.

de Bethune, X., Alfani, S., Lahaye, J. (1989). The influence of abrupt price increase on health utilisation: evidence from Zaire. *Health Policy & Planning,* **4**: 76-81.

de Savigny, D., Munna, G., Mbuya, C., Mgalula, L., Machibya, H., Mkikima, S., Mwageni, E., Kasale, H., Reid, G. (2001). *District health expenditure mapping: A budget analysis tool for Council Health Management Teams*. Tanzania Ministry of Health. Discussion Paper No. 1, October 2001.

de Silva, N.R., Brooker, S., Hotez, P.J., Montresor, A., Engels, D., Savioli, L. (2003). Soil-transmitted helminth infections: updating the global picture. *Trends in Parasitology*, **19**: 547-51.

de Vise, P. (1966). *Hospital study districts for metropolitan Chicago*. Technical Report No. 2, Hospital Planning Council for Metropolitan Chicago

de Wolf, T., Staal, S., Baltenweck, I. (2002). Just follow the road: testing GIS derived measures of farm market access. Unpublished.

Demery, L. (2000). *Benefits incidence: a practitioner's guide.* Washington: World Bank, Poverty and Social Development Group, Africa Region.

Development Solutions for Africa (1998). *Health and family planning: a geographic information analysis*. Reports of 16 districts prepared for the MoH/Division of Primary Health Care-UNDP, Nairobi.

Diamond, J. (2004).The Wealth of Nations. *Nature,* **429**: 616-617.

Diop, F., Seshamani, V., Mulenga, C. (1998). *Household health seeking behaviour in Zambia*. Partnerships for Health Reform, Maryland.

Division of Malaria Control (2004). *Replacing first-line anti-malarial therapy in Kenya in 2004*. Position paper developed by the Drug Policy Technical Working Group for Director Medical Services and Minister for Health, April 2004.

Dunn, C.E., Woodhouse, J., Bhopal, R.S., Acquilla, S.D. (1995). Asthma and factory emissions in northern England: addressing public concern by combining geographical and epidemiological methods. *Journal of Epidemiology & Community Health*, **49**: 395-400.

Dutt, A.K., Dutta, H.M., Jaiswal, J., Monroe, C. (1986). Assessment of service adequacy of primary health care physicians in a two county region of Ohio, USA. *Geo Journal,* **12**: 443–455.

Ensor, T. & Cooper, S. (2004). Overcoming barriers to health service access: influencing the demand side. *Health Policy & Planning,* **19**: 69-79.

Ensor, T. (1996). *Health sector reform in Asian transition countries: study on social sector issues in Asian transition economies*. University of York, York.

Falkingham, J. (2004). Poverty, out-of-pocket payments and access to health care: evidence from Tajikistan. *Social Science & Medicine,* **58**: 247-258.

Fein, R. (1954). Studies on physician supply and distribution. *American Journal of Public Health*, **44**: 615-624.

Fiedler, J.L. (1981). A review of literature on access and utilisation of medical care with emphasis on rural primary care. *Social Science & Medicine,* **15**: 129-142.

Field, K. S. & Briggs, D. J. (2001) Socio-economic and locational determinants of accessibility and utilization of primary health care, *Journal of Health and Social Care in the Community*, Special Issue: Geographies of primary care, 9 (5), pp294-308.

Fielding, A.H. & Bell, J.F. (1997). A review of the methods for the assessment of predictive errors on conservation presence/absence models. *Environmental Conservation*, **24**: 38-49.

Filmer, D. (2004). The incidence of public expenditures in health and education. http//econ.worldbank.org/wdr/wdr2004/library/doc?id=29478.

Frew, E., Wolstenholme, J.L., Atkin, W., Whynes, D.K. (1999). Estimating time and travel costs incurred in clinic based screening: flexible sigmoidoscopy screening for colorectal cancer. *Journal of Medical Screening,* **6**: 119-123.

Fritz F., Carver S., Linda S. (2000). *New GIS Approaches to Wild Land Mapping in Europe.* USDA Forest Proceedings RMRS-P-15-Vol-2.

Fryer, Jr., G.E., Drisko, J., Krugman, R.D., Vojir, C.P., Prochazka, A., Miyoshi, T.J., Miller, M.E. (1999). Multimethod assessment of access to primary medical care in rural Colorado. *Journal of Rural Health,* **15**: 113–121.

Gallup, J.C. & Sachs, D.J. (2001). The economic burden of malaria. *American Journal of Tropical Medicine and Hygiene,* **64 (Supplement 1)**: 85-96.

Garner, P. & Giddings, P. (1985). Rural health centre use: variations with distance and disease. *Papua New Guinea Medical Journal,* **30**:105-108.

Gertler, P., Locay, L., Sanderson, W. (1987). Are user fees regressive? *Journal of Econometrics,* **36**: 67-88.

Gething, P.W., Noor, A.M., Zurovac, D., Atkinson, P.M., Hay, S.I., Nixon, M.S., Snow, R.W. (2004). Empirical modeling of Government health service use by children with fevers in Kenya. *Acta Tropica,* **91**: 227-237.

Gilson, L. & Mills, A. (1995). *Health care reforms in sub-Saharan Africa. Lessons of the last ten years.* In: Health sector reform in developing countries, Berman, P. (eds.), Boston, Harvard University Press.

Gilson, L. (1998). In defence and pursuit of equity. *Social Science & Medicine,* **47**: 1891–1896.

Godlund, S. (1961). *Population, regional hospitals, transport facilities and regions: planning of location and regional hospitals in Sweden.* Royal University of Lund, Sweden, Department of Geography, Lund Studies in Geography, Series B. Human Geography, No. 21.

GoK (1998). *The Kenya Gazette.* The Government Printers, Nairobi, Kenya.

GoK (2004). *The National Social Insurance Fund Bill, 2004. Kenya Gazette Supplement No. 29 (Bills No. 10).* Bills 2004. 28th May 2004. pp. 1-52). Nairobi: Government of Kenya (GoK).

GoK-UNDP (2003). *Millennium Development Goals: progress report for Kenya.* Government of Kenya, Nairobi.

Greenwood, B.M., Greenwood, A.M., Bradley, A.K., Tulloch, S., Hayes, R., & Oldfield, F.S.J. (1987). Deaths in infancy and early childhood in a well-vaccinated, rural West African population. *Annals of Tropical Pediatrics,* **7**: 91-99.

Grossman, M. & Kaestner, R. (1997). Effects of education on health. In: Berhman, J.R., Stacey, N., (eds). *The Social Benefits of Education.* Ann Arbor, MI: University of Michigan Press.

Grubesic, T. (2000). Driving donation, a geographic analysis of potential organ donors in the state of Ohio, USA. *Social Science & Medicine,* **51**: 1197-1210.

Guargliardo, M.F., Ronzio, C.R., Cheung, I., Chacko, E., Joseph, J.G. (2004). Physician accessibility: an urban case study of pediatric providers. *Health & Place,* **10**: 273-283.

Guyatt, H.L., Noor, A.M., Ochola, S.A., Snow, R.W. (2004). Use of intermittent presumptive treatment and insecticide treated bed nets by pregnant women in four Kenyan districts. *Tropical Medicine & International Health,* **9**: 255-261.

Gwatkin, D. & Guillot, M. (2000). *The burden of disease among the global poor.* Washington, DC: International Bank for Reconstruction and Development/World Bank.

Gwatkin, D.R., Bhuiya, A., Victora, C.G. (2004). Making health systems more equitable. *Lancet,* **364**: 1273-1280.

Haddad, S., Fournier, P., Machouf, N., Yatara, F. (1998). What does quality mean to lay people? Community perception of Primary Health Care services in Guinea. *Social Science & Medicine,* **47**: 381-394.

Hagget, P. (1965). *Location Analysis in Human Geography.* Edward Arnold, London.

Haining, R. (1993). *Spatial Data Analysis in the Social and Environmental Sciences.* Cambridge University Press, Cambridge.

Hales, S., Chapman, P., Salmond, C., Woodward, A., Mackenbach, J. (1999). National infant mortality rates in relation to gross national product and distribution of income. *Lancet,* **354**: 2047-2048.

Hansen, W.G. (1959). How accessibility shapes land use. *Journal of the American Institute of Planners,* **25**: 73-76.

Hay, S.I., Snow, R.W., Roger D.L. (1998). Predicting malaria seasons in Kenya using multitemporal meteorological satellite sensor data. *Transactions of the Royal Society of Tropical Medicine & Hygiene,* **92**: 12-20.

Hay, S.I. (2000). An overview of remote sensing and geodesy for epidemiology and public health application. *Advances in Parasitology,* **47**: 1-35.

Hay, S., Guerra, C., Tatem, A., Noor, A., Snow, R. (2004). The global distribution and population at risk of malaria: past, present, and future. *Lancet Infectious Diseases,* **4**: 327-336.

Hay, S.I., Noor, A.M., Nelson, A., Tatem, A.J. (2005). Demography for epidemiology: the precision of large-area human population maps. *Tropical Medicine & International Health,* submitted.

Hewitt, A. & Tinline, R. (2004). *GIS and health care: spatial accessibility of cancer clinics in Hamilton, Ontario.* Department of Geography, Queen's University, Kingston, Ontario.

Hjorstberg, C.A. & Mwikisa, C.N. (2002). Cost of access to health services in Zambia. *Health Policy & Planning,* **17**: 71-77.

Jehlik, P.J. & McNamara, R.L. (1952). The relation of distance to the differential use of certain health personnel and facilities to the extent of bed illness. *Rural Sociology,* 17: 261-265.

Jones, G., Steketee, R.W., Black, R.E., Bhutta, Z.A., Morris, S.S., Group, Bellagio Child Survival Study Group (2003). How many child deaths can we prevent this year? *Lancet,* **362**: 65-71.

Jonkman, A., Chibwe, R.A., Khoromana, C.O., Liabunya, U.L., Chaponda, M.E., Kandiero, G.E., Molyneux, M.E., & Taylor, T.E. (1995). Cost-saving through microscopy-based versus presumptive diagnosis of malaria in adult outpatients in Malawi. *Bulletin of the World Health Organization,* **73**: 223-227.

Jordan, H., Roderick, P., Martin, D., Barnett, S. (2004). Distance, rurality and the need for care: access to health services in South West England. *International Journal of Health Geographics*, **3**: 21.

Joseph, A. E. & Bantock, P. R. (1982). Measuring potential physical accessibility to General Practitioners in rural areas. *Social Science & Medicine,* **16**: 85-90.

Khan, A.A. & Bhardwaj, S.M. (1994). Access to health care. A conceptual framework and its relevance to health care planning. *Evaluation & the Health Professions,* **17**: 60-76.

Khan, M.A., Walley, J.D., Witter, S.N., Imran, A., Safdar, N. (2002). Cost and cost-effectiveness of different DOTS strategies for treatment of tuberculosis in Pakistan. *Health Policy & Planning,* **17**: 178-186.

Kirkwood BR & Sterne JAC (2003) *Essential Medical Statistics*. Blackwell Publishing, London.

Kohli, S., Sahlén, K., Sivertun, Å., Löfman, O., Trell, E., Wigertz, O. (1995). Distance from the primary health centre: a GIS method to study geographical access to health care. *Journal of Medical Systems,* **19**: 425-436.

Kumaran, V.V. (1983). Location, use, and locational efficiency of health facilities in a Madras neighbourhood. *Geographia Medica,* **13**: 53-65.

Langmuir, E. (1984). *Mountain craft and Leadership*. The Scottish Sport Council/MLTB, Cordee, Leicester.

Lassey, M.L., Lassey, W.R., Jinks, J.M. (1997). *Health care systems around the world: characteristics, issues, reforms.* Prentice-Hall, Inc. New Jersey. Pages 370.

Le Sueur, D., Ngxongo, S., Sharp, B., Martin, C., Fraser, C., Teuschner, M., Tollman, S., Green, C., Tsoka, J., Solarsh, G., Mnzava, A. (1997). *Towards a Spatial Rural Information System.* National Malaria Research Programme, MRC, Durban; Department of Health,, KwaZulu/Natal; Health Systems Development Unit, University of Witwatersrand, Arconhoek; Department of Paediatrics, University of Natal. Kwik Kopy Printing, Durban.

Lee, D.B. (1973). Requiem of large scale models. *Journal of American Institute of Planners*, **39**: 163-168.

Lengeler, C. (2001). Comparison of malaria control interventions. *Bulletin of the World Health Organization*, **79**: 77.

Leon, D., Walt, G., Gilson, L. (2001). International perspectives on health inequality and policy. *British Medical Journal,* **322**: 591-594.

Leonard, K.L., Mliga, J.R., Mariam, D.H. (2002). *Bypassing health centres in Tanzania: revealed preferences for observable and unobservable quality*. Department of Economics, Discussion Paper Series. New York, Columbia University.

Lin, Z., Oguchi, T., Duan, F. (1999). Topographic and climatic influences on population and soil in East and South-East Asia: A GIS Approach. *Geographic Review of Japan*, **72B:** 181-192.

Lively, C.E. & Beck, P.G. (1927). The rural health facilities of Ross County, Ohio. *Wooster: Ohio AES Bulletin,* **412**: 45-46.

Landis, J. & Koch, G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, **33**: 159-174.

Loslier, L. (1994). *GIS for Health and the Environment. Proceedings of an international workshop held in Colombo, Sri Lanka, 5-10, September 1994.* Edited by Don de Savigny & Wijeyaratne, P., IDRC, 1995.

Low, A., Ithindi, T., Low, A. (2003). A step too far? Making health equity interventions in Namibia more sufficient. *International Journal for Equity in Health,* **2**: 5.

Lucas, C. & Rosenthal, T. (1992). Access to health care in rural western New York State. *New York State Journal of Medicine*, **92**: 465-469.

Lule, G., Tugumisirize, J., Ndekha, M. (2000). Quality of care and its effects on utilization of maternity services at health centre level. *East African Medical Journal*, **77**: 250 - 255.

Luo, W. (2004). Using a floating-catchment based method to assess areas with shortage of physicians. *Health & Place*, **10**: 1-11.

Macinko, J.A. & Starfield, B. (2002). Annotated bibliography on equity in health, 1980-2001. *Internal Journal for Equity in Health,* **1**:1.

Makinen, M., Waters, H., Rauch, M., Almagambetova, N., Bitran, R., Gilson, L., Mclntyre, D., Prieto, A.L., Ubilla, G., Ram, S. (2000). Inequalities in health care use and expenditures: Empirical data from eight developing countries and countries in transition. *Bulletin of World Health Organization,* **78**: 55-65.

Martin, D., Wrigley, H., Barnett, S., Roderick, P. (2002). Increasing the sophistication of access measurement in a rural healthcare study. *Health & Place*, **8**: 3-13.

Mather, W.G. (1948). The use of health services in two Southern Pennsylvania communities. *Pennsylvania AES Bulletin,* 504

Mbarki, L., Ben Salah, A., Chlif, S., Chahed, M.K., Balma, A., Chemama, N., Garraoui, A., Ben-Ismail, R. (1995). *Monitoring zoonotic cutaneous leishmaniasis with GIS. GIS for Health and Environment*. Proceedings of an International Workshop held in Colombo, Sri Lanka, 5-10 September 1994. De Savigny & Wijeyaratne (eds.), IDRC.

Mburu, F.M. (1980). *Health Development in Kenya, 1964-1978: Issues of relevance and priority*. Department of Community Health, University of Nairobi.

McCormick, T.C. (1934). Rural social organisation in South Central Arkansas. *Fayetteville: Arkansas AES Bulletin*, **313**: 29.

McFadden, D.L. & Sunkara, V. (2004). The educative impact of health care treatment on malarial prevention behaviour for the poor in Guinea, West Africa. *Proceedings of the National Academy of Sciences*, **101**: 11523-11525.

Mclntyre, D. & Gilson, L. (2000). Redressing disadvantage: promoting vertical equity within South Africa. *Health Care Analysis,* **8**: 235–58.

Mcintyre, D., Muirhead, D., Gilson, L. (2002). Geographic patterns of deprivation in South Africa: informing health equity analyses and public resource allocation strategies. *Health Policy and Planning* **17**: 30-39.

McNamara, R. & Hassinger, E. (1956). The pattern of medical services for incorporated places of 500-or-more population in Missouri, 1950. *Rural Sociology*, **21**: 175-177.

McPherson, J.M., Jetz, W., Rogers, D.J. (2004). The effects of species' range sizes on the accuracy of distribution models: ecological phenomenon or statistical artefact? *Journal of Applied Ecology*, **41**: 811-823.

Ministry of Health (1994). *Health Policy Framework.* Government of Kenya, Nairobi, Kenya.

Mkawagile, D.S.M., & Kihamia, C.K. (1986). Relationship between clinical Diagnosis of malaria and parasitaemia in Adult patients attending Mwananyamala dispensary, Dar-es-salaam. *The Central African Medical Journal*, **32**: 2-8.

MoH (1999). *National Health Sector Strategy Plan.* Government of Kenya, Nairobi, Kenya.

MoH (2001). *National Malaria Strategy: 2001-2010.* Division of Malaria Control. Ministry of Health, Government of Kenya, April 2001.

MoH (2002). *Guidelines for the District Health Management Boards & Health Centre Management Committees.* Ministry of Health, Government of Kenya, Nairobi.

MoH (2004a). *Kenya Expanded Programme on Immunisation: Year 2005 operation workplan for integrated immunization campaign (Measles, OPV, Vitamin A and LLTINs) in Kenya.* Ministry of Health, Government of Kenya, Nairobi.

MoH (2004b) *Sessional Paper No. 2 of 2004 on National Social Health Insurance in Kenya, May 2004. Theme: Providing Quality healthcare for all Kenyans.* Ministry of Health (MoH), Republic of Kenya, Nairobi.

Molyneux, C.S., Mung'ala-Odera, V., Harpham, T., Snow, R.W. (1999). Maternal responses to childhood fevers: a comparison of rural and urban residents in coastal Kenya. *Tropical Medicine & International Health,* **4**: 836-845.

Müller, I., Smith, T., Mellor, S., Rare, L. Genton, B. (1998). The effect of distance from home on attendance at a small rural health centre in Papua New Guinea. *International Journal of Epidemiology*, **27**: 878-884.

Mwabu, G. (1995). Health care reform in Kenya: a review of the process. *Health Policy*, **32**: 245-255.

Mwenesi, H.R.A. (1993). *Mothers' definition and treatment of childhood malaria on the Kenya coast.* University of London, London.

Mwenesi, H.R.A., Harpham, T., Snow, R.W. (1995). Child malaria treatment practices among mothers in Kenya. *Social Sciences Medical Journal*, **40**: 1271-1277.

Narayan, D. (1997). *Voices of the poor: poverty and social capital in Tanzania.* ESD studies and Monograph series No. 20. The World Bank, Washington, DC.

National Council for Population Development (2003). *Kenya demographic and health survey.* Central Bureau of Statistics, Nairobi.

Ndyomugyenyi, R., Neema, S., Magnussen, P. (1998). The use of formal and informal services for antenatal care and malaria treatment in rural Uganda. *Health Policy and Planning*, 13(1): 94-102.

Nobre, F.F., Braga, A.L., Pinheiro, R.S., Lopes J.A.S. (1997). GISEpi: a simple geographical information system to support public health surveillance and epidemiological investigations. *Computer Methods & Programs in Biomedicine*, **53**: 33-445.

Noor, A.M., Zurovac, D., Hay, S.I., Ochola, S.A., Snow, R.W. (2003). Defining equity in physical access to clinical services using geographical information systems as part of malaria planning and monitoring in Kenya. *Tropical Medicine & International Health*, **8**: 917-926.

Noor, A.M., Gikandi, P.W., Hay, S.I., Muga, R.O., Snow, R.W. (2004). Creating spatially defined databases for equitable health service planning in resource poor countries: the example of Kenya. *Acta Tropica*, **91**: 239-251.

Noorali, R., Luby, S., Rahbar, M.H. (1999). Does use of a government service depend on distance from the health facility? *Health Policy & Planning*, **14**: 191-197.

Nyamongo, I. (2002). Health Care switching behaviour of malaria patients in a Kenyan rural Community. *Social Science & Medicine*, **54**: 377-386.

O'Dempsey, T., McArdle, T., Laurence, B., Lamont, A., Todd, J., & Greenwood, B. (1993). Overlap in the clinical features of pneumonia and malaria in African children. *Transactions of the Royal Society of Tropical Medicine & Hygiene*, **87**: 662-665.

Ojany, F.F., & Ogendo, R.B. (1988). *Kenya: a study in physical and human geography* Nairobi: Longman.

Olaleye, B.O., Williams, L.O., D' Alessandro, U., Weber, M.M., Mulholland, K., Okorie, C., Langerlock, P., Bennett, S., Greenwood, B.M. (1998). Clinical predictors of malaria in Gambian children with fever or a history of fever. *Transactions of the Royal society of Tropical Medicine & Hygiene*, **92:** 300-304.

Omumbo, J., Guerra, C., Hay, S., Snow, R. (2005). The influence of urbanisation on measures of Plasmodium falciparum infection prevalence in East Africa. *Acta Tropica*, **93**: 11-21.

Omumbo, J., Hay, S., Goetz, S., Snow, R., Rogers, D. (2002). Updating historical maps of malaria transmission intensity in East Africa using remote sensing. *Photogrammetric Engineering & Remote Sensing*, **68**: 161-166.

Omumbo, J., Hay, S., Guerra, C., Snow, R. (2004). The relationship between the Plasmodium falciparum parasite ratio in childhood and climate estimates of malaria transmission in Kenya. *Malaria Journal*, **17**:3(1)

Openshaw, S. (1996). Geographical Information Systems and tropical diseases. *Transactions of the Royal Society of Tropical Medicine & Hygiene*, **90**: 337-339.

Owino, W. & Munga, S. (1997). *Decentralization of financial management systems: Its implementation and impact on Kenya health care delivery*. Institute of Analysis and Research, Nairobi, DP No. 006/1997, pages. 1- 42

Oyaya, C., & Rifkin, S. (2003). Health sector reforms in Kenya: an examination of district level planning. *Health Policy*, **64**: 113-127.

Penchansky, R. & Thomas, J.W. (1981). The concept of access: definition and relationship to consumer satisfaction. *Medical Care*, **19**: 127-140.

Penchansky, R. (1977). *The concept of access: a definition.* National Health Planning Information Centre, Hyattsville, Maryland (HRP-0900113)

Perry, B. & Gesler, W. (2000). Physical access to primary health care in Andean Bolivia. *Social Science & Medicine*, **50**: 1177-1188.

Phibbs, C.S. & Luft, H.S. (1995). Correlation of travel time on roads versus straight line distance. *Medical Care Research & Review*, **52**: 532–542.

Piette, J.D. & Moos, R.H. (1996). The influence of distance on ambulatory care use, death and readmission following a myocardial infarction. *Health Services Research*, **31**: 573-591.

Pillai, R., Williams, S.V., Glick, H.A., Polsky, D., Berlin, J.A., Lowe, R.A. (2003). Factors affecting decisions to seek treatment for sick children in Kerala, India. *Social Science & Medicine,* **57**: 783-790.

Phillips-Howard, P., Ter kuile, F., Nahlen, B., Alaii, J., Gimnig, J., Kolczak, M., Terlouw, D., Kariuki, S., Shi, Y., Kachur, S., Hightower, A., Vulule, J., Hawley, W. (2003). The efficacy of permethrin-treated bed nets on child mortality an morbidity in western Kenya II study design and methods. *American Journal of Tropical Medicine & Hygiene*, **35**: 10-15.

Pokhrel S. & Sauerbron, R. (2004). Household decision-making on child health care in developing countries: the case of Nepal. *Health Policy & Planning*, **19**: 218-233.

Raghupathy, S. (1996). Education and the use of maternal health care in Thailand. *Social Science & Medicine,* **43**: 459-471.

Rashid, S.F., Hadi, A., Afsana, K., Begum, S.A. (2001). Acute respiratory infections in rural Bangladesh: cultural understandings, practices and the role of mothers and community health volunteers. *Tropical Medicine & International Health,* **6**: 249-255.

Redd, S.C., Bloland, P.B., Kazembe, P.N., Patrick, E., Tembenu, R., & Campbell, C.C. (1992). Usefulness of clinical case-definitions in guiding therapy for African children with malaria or pneumonia. *The Lancet*, **340**: 1140-1143.

Richards, T.B., Croner, C.M., Rushton, G., Brown, C.K., Fowler, L. (1999). Geographic information systems and public health: mapping the future. *Public Health Report,* **114**: 359-73.

Robinson, T. (1998). Geographic Information Systems and the selection of priority areas for control of tsetse-transmitted trypanosomiasis in Africa. *Parasitology Today*, **14**: 457-461.

Rosero-Bixby, L. (2004). Spatial access to health care in Costa Rica and its equity: a GIS-based study. *Social Science & Medicine*, **58**: 1271-1284.

Rous, J.J. & Hotchkiss, D.R. (2003). Estimation of the determinants of household health care expenditures in Nepal with controls for endogenous illness and provider choice. *Health Economics.* **12**: 431-51.

Sachs, J. D., McArthur, J.W. (2005). The Millennium Project: a plan for meeting the Millennium Development Goals. *Lancet,* **365**: 347-353.

Sauerborn, R., Ibrango, I., Nougtara, A., Borchert, M., Hien, M., Benzler, J., Koob, E., Diesfeld, H.J. (1995). The economic costs of illness for rural households in Burkina Faso. *Tropical Medicine & Parasitology* **46**: 54-60.

Scholten, H.J. & de Lepper, M.J.C. (1991). The benefits of the application of geographical information systems in public and environmental health. *World Health Quarterly*, **44**: 160-169.

Schwartz, J.B., Akin, J.S., Popkin, B.M. (1993). *Economic determinants of demand for modern infant-delivery in low-income countries: the case of the Phillipines.* In: Mills, A., Lee, K. (eds.). Health economic research in developing countries. Oxford and New York. Oxford Medical Publications.

Shannon, G.W., Bashshur, R.L. Metzner, C.A. (1969). The concept of distance as a factor in accessibility and utilisation of health care. *Medical Care Review,* **26**: 143-161.

Armstrong-Schellenberg, J., Victora, C., Mushi, A., de Savigny, D., Schellenberg, D., Mshinda, H., Bryce, J., T.I.M.B.H.S.S. group (2003). Inequities among the poor: health care for children in rural southern Tanzania. *The Lancet*, **361**: 561-566.

Sim, J. & Wright, C.W. (2005). The Kappa Statistic in Reliability Studies: Use, Interpretation, and Sample Size Requirements. *Physical Therapy*, **85**: 257-268.

Smith, T.R., Menson, S., Starr, J.L., Estes, J.E. (1987). Requirements and principles for the implementation and construction of large-scale geographic information systems. *International Journal of Geographic Information Systems*, **1**: 13-31.

Snow, R.W., Peshu, N., Forster, D., Mwenesi, H., Marsh, K. (1992). The role of shops in the treatment and prevention of childhood malaria on the coast of Kenya. *Transactions of the Royal Society of Tropical Medicine & Hygiene,* **86**: 237-239.

Snow, R.W., Schellenberg, J.R.M.A., Forster, D., Mungala, V.O., Marsh, K. (1994). Factors influencing admission to hospital during terminal childhood illnesses in Kenya. *International Journal of Epidemiology*, **23**: 1013-1019.

Snow, R.W., Marsh, K., Le Sueur, D. (1996). The need for maps of transmission intensity to guide malaria control in Africa. *Parasitology Today*, **12**: 455-457.

Snow, R.W., Gouws, E., Omumbo, J., Rapuoda, B., Craig, M.H., Tanser, F.C., le Sueur, D., Ouma, J. (1998). Models to predict the intensity of *Plasmodium falciparum* transmission: applications to the burden of disease in Kenya. *Transactions of the Royal Society of Tropical Medicine & Hygiene*, **92**: 601-606.

Snow, R.W., Craig, M., Deichmann, U., Marsh, K. (1999). Estimating mortality, morbidity and disability due to malaria among Africa's non-pregnant population. *Bulletin of World Health Organization,* **77**: 624-640.

Snow, R.W., Craig, M., Newton, C., Steketee, R. (2003). *The public health burden of plasmodium falciparum malaria in Africa: Deriving the numbers.* Kemri-Wellcome Trust collaborative programme, Nairobi. Pages 1-68. (www.fic.nih.gov/dcpp/).

Sutrisna, B., Reingold, A., Sudarti, K., Harrison, G., Utomo, B. (1993). Care-seeking for fatal illnesses in young children in Indramayu, West Java, Indonesia. *Lancet*, **342**: 787-789.

Talen, E. & Anselin, L. (1998). Assessing spatial equity: an evaluation of measures of accessibility to public playgrounds. *Environment and Planning A*, **30**: 595–613.

Tanser, F. & Wilkinson, D. (1999) *Improved access to Tuberculosis treatment in rural Africa: A novel application of geographical information system and global positioning system technologies*. Australia: University of South Australia.

Tanser, F.C., Hosegood, V., Benzler, J. Solarsh, G. (2001). New approaches to spatially analyse primary health care usage patterns in rural South Africa. *Tropical Medicine & International Health*, **6**: 826-838.

Task Force for Health Systems Research (2004). Informed choices for attaining the millennium development goals: towars an international cooperative agenda for health systems research. *Lancet*, **364**: 997-1003.

Tatem, A.J., Noor, A.M., Hay, S.I. (2004). Defining approaches to settlement mapping for public health management in Kenya using medium spatial resolution satellite imagery. *Remote Sensing of Environment*, **93**: 42-52.

Tatem, A.J., Noor, A.M., Hay, S.I. (2005). Accuracy of urban area delineation in Kenya. *Remote Sensing of Environment,* submitted for peer review 12-10-04. Manuscript ID: RSE-D-04-00927

Terris, M. & Mary, A. (1956). Recent trends in the distribution of physicians in Upstate New York. *American Journal of Public Health*, **46**: 585-591.

Thaden, J.F. (1951). *Distribution of doctors of medicine and osteopaths in Michigan communities*. Michigan State College. AES, Department of Sociology and Anthropology and Social Research Service, Special Bulletin, page 370.

The Standard (2004). *New drug to treat malaria unveiled*. East African Standard, Thursday 22nd April, 2004.

Thorson, A., Hoa, N.P., Long, N.H. (2000). Health-seeking behaviour of individuals with cough for more than 3 weeks. *Lancet,* **356**: 1823-1824.

Travis, P., Bennett, S., Haines, A., Pang, T., Bhutta, Z.H., Hyder, A.A., Pielemeier, N.R., Mills, A., Evans, T. (2004). Overcoming health-systems constraints to achieve the Millennium Development Goals. *Lancet*, **364**: 900-906.

Turrel, G. & Mathers, C. (2001). Socioeconomic inequalities in all-cause and specific-cause mortality in Australia: 1985–1987 and 1995–1997. *International Journal of Epidemiology,* **30**: 231–9.

Twigg, L. (1990). Health based geographical information systems: Their potential in the light of existing data sources. *Social Science & Medicine,* **30**: 143-155.

Uebersax, J.S. (1987). Diversity of decision-making models and the measurement of interrater agreement. *Psychological Bulletin*, **101**: 140-146.

UN (2000). *United Nations millennium declaration*. United Nations General Assembly, A/RES/55/2. (www.un.org).

UN (2001). *Road map towards the implementation of the United Nations millennium declaration.* United Nations General Assembly, A/56/326. (www.un.org).

UN (2002). *Report of the International Conference on Financing for developmet.* United Nations, A/CONF. 198/11, Monterrey, Mexico, 18-22 March 2002. (www.un.org).

UN (2004). *High-level dialogue on financing for development.* A/57/CRP,5, United Nations, New York. (www.un.org).

UN (2005). *Investing in development: a practical plan to achieve the Millennium Development Goals.* UN Millennium Project, New York. (www.un.org).

UNDP (2003). *Human Development Report- Millennium Development Goals: a compact among nations to end human poverty.* UNDP, New York. (www.un.org).

U.S. Public Health Service (1961). *Areawide planning for hospitals and related health facilities.* PHS publication No. 855, U.S. Government Printing Office, Washington DC.

van Doorslaer, E., Wagstaff, A., van der Burg, H., Christiansen, T., De Graeve, D., Duchesne, I., Gerdtham, U.G., Gerfin, M., Geurts, J., Gross, L., Hakkinen, U., John, J., Klavus, J., Leu, R.E., Nolan, B., O'Donnell, O., Propper, C., Puffer, F., Schellhorn, M., Sundberg, G., Winkelhake, O. (2000). Equity in the delivery of health care in Europe and the US. *Journal of Health Economics,* **19**: 553–83.

Vandervoort, D. (1999). ProxSpid.ave. (www.esri.com/arcscripts).

Victora, C., Wastaff, A., Schellenberg, J., Gwatkin, D., Claeson, M., Habicht, J.P. (2003). Applying an equity lens to child health and mortality: more of the same is not enough. *Lancet,* **362**: 233-241.

Victora, C.G., Hanson, K., Bryce, J., Vaughn, J.P. (2004). Achieving universal coverage with health interventions. *Lancet,* **364**: 1541-1548.

Waddington, C.J. & Enyimayew, K.A. (1989). A price to pay: the impact of user charges in Ashanti-Akim district, Ghana. *International Journal of Health Planning & Management,* **4**: 17 - 47.

Wang, F. & Luo, W. (2004). Assessing spatial and aspatial factors for health care access: towards an integrated approach to defining health professional shortage areas. *Health & Place.*

Waters, H. (2000). Measuring equity in access to health care. *Social Science & Medicine,* **51**: 599–612.

Whitehead, M. (1993). *Is it fair? Evaluating the equity implications of the NHS reforms.* In: Evaluating the NHS reforms. Robinson R., Le Grand J. (eds.). London, Kings Fund.

WHO (1978). P*rimary health care. Report of the international conference on Primary Health Care, Alma Ata, 6-12 September 1978.* Geneva, Switzerland.

WHO (1986). World malaria situation 1984. *World Health Statistic Quarterly,* **39**: 171-205.

WHO (1996a). *Equity in health and health care.* WHO/ARA/96.1. World Health Organization, Geneva, Switzerland.

WHO (1996b). *Investing in health research and development: a report of the adhoc committee in health research relating to future intervention options*. World Health Organization, Geneva, Switzerland. Pages 278.

WHO (2000). *World Health Report: Health Systems: Improving Performance.* World Health Organization, Geneva, Switzerland. Pages 206.

WHO (2001). *Macroeconomics and health: investing in health for economic development*. Report of the commission on macroeconomics and health, World Health Organization, Geneva, Switzerland. Pages 202.

WHO (2003). *Success in Africa: The Onchocerciasis Control Programme in West Africa, 1974-2002.* World Health Organization, Geneva, Switzerland. Pages 1- 79.

Wilderness Tech Tips, (1998). URL: http://www.edgeinternet.com/wtc/tips.htm

Wilson, A.G. (1967). A statistical theory of spatial distribution models. *Transportation Research*, **1**: 253-269.

Wilson, I.C. & Metzler, W.H. (1938). Sickness and medical care in an Ozark area in Arkansas. *Fayetteville: Arkansas AES Bulletin,* **353**: 37-38.

Wint, G.R.W., Robinson, T.P., Bourn, D.M., Durr, P.A., Hay, S.I., Randolph, S.E., Rogers, D.J. (2002). Mapping bovine tuberculosis in Great Britain using environmental data. *Trends in Microbiology*, **10**: 441-444.

World Bank (1993). *World Development Report: Investing in Health.* Oxford University Press, New York, pages 319. (http://publications.worldbank.org/)

World Bank (2001). *African Development Indicators.* Washington DC, pages 366. (http://publications.worldbank.org/)

World Bank (2003). *World Development Indicators*. World Bank, Washington. Pages 58-61. (http://publications.worldbank.org/)

World Bank (2004a). *The Millennium development goals for health: rising to the challenges.* World Bank, Washington. Pages 186. (http://publications.worldbank.org/)

World Bank (2004b). *World Development Report: Making services work for the poor.* World Bank, Washington. Pages 271. (http://publications.worldbank.org/)

Wright, D. J., Goodchild M. F., Proctor, J. D. (1997). GIS: tool or science? Demystifying the persistent ambiguity of GIS as "tool" versus "science". *Annasl of the Association of American Geographers*, **87**: 346-362.

Yanagisawa, S., Mey, V., Wakai, S. (2004) Comparison of health-seeking behaviour between poor and better-off people after health sector reform in Cambodia. *Public Health*, **118**: 21-30.

Yoder, R.A. (1989). Are people willing and able to pay for health services? *Social Science & Medicine*, **29**: 35-42.

Zurovac, D., Midia, B., Ochola, S.A., Barake, Z., Snow, R.W. (2002). *The evaluation of malaria case management of sick children presenting in out-patient departments in*

Government health facilities in Kenya. Report submitted to the Division of Malaria Control, Ministry of Health, Government of Kenya.

Zurovac, D., Rowe, A., Ochola, S.A., Noor, A.M., Midia, B., English, M., Snow, R.W. (2004). Predictors of the quality of health worker treatment practices for uncomplicated malaria in Government health facilities in Kenya. *International Journal of Epidemiology*, **33**: 1080-1091.

Zwarenstein, M., Krige, D., Wolff, B. (1991). The use of a geographical information-system for hospital catchment-area research in Natal Kwazulu. *South African Medical Journal*, **80**: 497-500.

APPENDICES

Appendix 1: Health Facility Questionnaire

Code [__]-[__ __ __]

1. Date .... [_|_][_|_][_|_]
2. Health Facility Name .... [________________]
3. District .... [________________]
4. Division .... [________________]
5. Longitude .... [_]-[_|_]-[_|_|_|_|_|_]
6. Latitude .... [_]-[_|_]-[_|_|_|_|_|_]
7. Name of Contact Person .... [________________]
8. Postal Address .... [________________]
9. Physical Address(Street, etc) .... [________________]
10. Telephone Numbers .... [_|_|_|_]-[_|_|_|_|_|_]

+[_|_|_|_]-[_|_|_|_|_|_]

+[_|_|_|_]-[_|_|_|_|_|_]

11. Fax Numbers .... [_|_|_|_]-[_|_|_|_|_|_]
12. Email Address .... [________________]

13. Health Facility Type: *(Tick where appropriate.)*

District Hospital .... [_]
Private Hospital .... [_]
Specialist Hospital, Specify .... (________) [_]
Armed Forces Hospital .... [_]
Other Hospital .... [_]
Health Centre or Sub-Health Centre .... [_]
Dispensary .... [_]
Other Clinic .... [_]
Maternity Home .... [_]
Training Facility .... [_]
Bamako Initiative Site or Community Pharmacy .... [_]
Training Facility .... [_]

14. Agency: *(Tick where appropriate)*

Ministry of Health .... [_]
Mission .... [_]
NGO .... [_]
Local Authority .... [_]
Private .... [_]
Armed Forces .... [_]

15. If Mission or NGO specify the Church or Organisation ... [________________]

A. PERSONNEL:

How many of the following cadres of personnel work in the facility?

Doctors .... [_|_]
How many Doctors are Specialists in
Obstetrics .... [_|_]
Paediatrics .... [_|_]

Clinical Officers .... [__|__|__]
How many clinical officers are specialists in
Obstetrics .... [__|__]
Paediatrics .... [__|__]

Registered Nurses.. [__|__|__]
Enrolled Nurses .... [__|__|__]
Laboratory Technologist .... [__|__]
Laboratory Technician .... [__|__]
Pharmacist .... [__]
Pharmaceutical Technologist .... [__]
Public Health Officer .... [__|__]
Public Health Technician .... [__|__]
Health Information Systems (HIS) Officer .... [__]
Other Technical Staff .... [__]
Support Staff (non-technical) .... [__|__]

B: UTILITY:

1. How many beds does the facility have?

Paediatric .... [__|__|__]
Adult Male .... [__|__|__]
Adult Female .... [__|__|__]
Maternity .... [__|__|__]
Other (Specify) ....(______________________) [__|__|__]

Does the Facility have running water? (Y/N) .... [__]

Does the Facility have electricity? (Y/N) .... [__]

Does the Facility provide Laboratory services? (Y/N) .... [__]

2. Is malaria microscopy available?(Y/N) .... [__]

If yes, what is the type of microscopy? (Y/N) ....
Light .... [__]
Electric .... [__]

Does the facility have an ambulance?(Y/N) .... [__]

How many vehicles does the facility have and how many are functioning?
Total Number of Vehicles .... [__|__]
Number functioning at present .... [__|__]

C: SERVICES:

Does the facility provide the following services? (Y/N)

Integrated Management of Childhood Illnesses (IMCI) .... [__]

Antenatal Services.. [__]

Expanded Program on Immunisation (EPI) .... [__]

Growth Monitoring services .... [__]

Does the facility provide bed-nets... [__]

Does the facility provide services for insecticide treatment of bed-nets .... [__]

Blood Transfusion.. [__]

Pharmacy.. [__]

Appendix 2: Health facility based survey on the use and cost services for the treatment of paediatric fevers

Mother/caretaker interview [__]-[__|__|__]-[__]-[__|__|__]

1. Child's Residence:

District..[________________________]
Location..[________________________]
Sub-location ....[________________________]
Enumeration Area/Village ....[________________________]
Household heads name...........................[________________________]
Clan elder's/ Village Head's name ....[________________________]
Nearest school.................................[________________________]
Nearest bus stage..............................[________________________]
Nearest shop name..............................[________________________]
Nearest HF name................................[________________________]
To be completed later:
Confirmed EA ....[________________________] – [__|__|__|__]

2. Is **the first attendance** at this facility for this illness episode(Y/N) ....[__]

3. How much money did mother pay for:
Laboratory examinations (KES) .... [__|__|__|__]
Drugs (KES)...[__|__|__|__]
Consultation (KES)..[__|__|__|__]
Transport (one way fare) (KES)..[__|__|__|__]
Total Cost (KES).. [__|__|__|__]

4. Does your child's present illness involve a **fever**? (Y/N)..[__]

If No, end interview If Yes, Continue

5. For **how many days** has the child had a fever (Today = 1).....................................[__|__]

6. **Before** the child was brought to this HF did s/he receive **any other treatment** (Y/N) [__]

If yes,
7. *What was the first treatment (s) given to the child and its cost – unprompted (see drug chart)*
[____________________] ....[__|__][__|__|__]
[____________________] ....[__|__][__|__|__]
[____________________] ....[__|__][__|__|__]
[____________________] ....[__|__][__|__|__]

[__]-[__|__|__]-[__]-[__|__|__]

8. What was the **total cost** of treatment, tests and consultation the mother had to pay at this point of intervention (KES).. [__|__|__]
9. Where were these **drugs obtained from**

1.drugs kept at home; 2. shop; 3. private pharmacist; 4. private doctor; 5. community pharmacist (e.g. BI); 6. government dispensary, health centre or hospital; 7. mission dispensary, health centre or hospital; 8. other (specify________________)..............[__]

10. Provide **name** of shop or facility[____________________]...... [__]-[__|__|__|__]

11. Were any **other treatments given after** this treatment (Y/N) ....[__]

If yes, complete additional sheet

Caretaker - supplementary sheet

1. Is this the **1.** Second; **2.** Third; **3.** Fourth or **4.** Fifth treatment since the illness began before attending the present facility...[__]

2. What were the treatment (s) given to the child and its cost – unprompted (see drug chart)

[____________________] ....[__|__][__|__|__]
[____________________] ....[__|__][__|__|__]
[____________________] ....[__|__][__|__|__]
[____________________] ....[__|__][__|__|__]

3. What was the **total cost** of treatment, tests and consultation the mother had to pay at this point of intervention (KES)... [__|__|__]

4. Where were these drugs obtained from
1.drugs kept at home; 2. shop; 3. private pharmacist; 4. private doctor; 5. community pharmacist (e.g. BI); 6. government dispensary, health centre or hospital; 7. mission dispensary, health centre or hospital; 8. other (specify________________.) [__]

5. Provide name of shop or facility [____________________] .... [__]-[__|__|__|__]

6. How many days ago was this treatment given (today = 01) .... [__|__]

7. Were any other treatments given after this treatment (Y/N)...[__]

If yes, complete additional sheet

Appendix 3: Household malaria prevention and morbidity survey

Section 1: Household geography and demographics

1. Today's date .... [__|__]-[__|__]-[__|__]
2. Enumerator's Name & Code......... [________________________________][__|__|__]

3. Enumeration Area .... [________________________________][__|__|__]
4. Sub-location .... [________________________________][__|__|__]
5. District................................ [________________________________][__]

6. Homestead Head's Name................[________________________________]
7. Homestead Number (District-EA-Number)............................... [__]-[__|__|__]-[__|__|__]
8. Longitude ....[__]-[__|__]-[__|__|__|__|__]
9. Latitude ....[__]-[__|__]-[__|__|__|__|__]

By interviewing a key respondent in the household and observation establish the following:

10. Total number of sleeping rooms within homestead ....[__|__]

11. Total number of beds/sleeping mats in the homestead ....[__|__]

12. Total number of beds/sleeping mats in the homestead usually covered by a bed net
....[__|__]

13. Total number of children <u>less</u> than 5 years old resident within the homestead ......[__|__]

14. Total number of children aged 5-9 years resident within the homestead ....[__|__]

15. Total number of children aged 10-14 years resident within the homestead ....[__|__]

16. Total number of people aged 15 years or older resident within the homestead......[__|__]

17. Total number of people resident within the homestead ....[__|__]

18. Total number of women currently pregnant and resident within the homestead....[__|__]

District-Enumeration-Household number –[__]-[__|__|__]-[__|__|__]

19. Total number of bed nets currently used by people in the household.................... [__|__]

20. Total number of people usually sleeping under a bed net...................................... [__|__]

21. Total number of children less than 5 years old usually sleeping under a bed net... [__|__]

22. Total number of pregnant women usually sleeping under a bed net...................... [__|__]

23. How many bed nets have been treated with an insecticide during the last 6 months
.... [__|__]

24. Have any sleeping rooms been sprayed with insecticide during the preceding
12 months (Y/N) ....[__]
If yes, how many sleeping rooms [__|__]
Date of last spraying (mm-yy) [__|__]-[__|__]

25. Have any members of the household attended a barazaar or meeting on malaria
in the last 12 months (Y/N)..[__]
If yes, date of last meeting (mm-yy) [__|__]-[__|__]

26. Has any member of the household received any printed materials related to malaria
prevention or control in the last 12 months (Y/N)..[__]
If yes, describe materials [________________________][__|__]
Date these were received by the household member (mm-yy)................ [__|__]-[__|__]

District-Enumeration-Household number –[__]-[__|__|__]-[__|__|__]

Section 2: Childhood fevers

Identify all resident children below 5 years of age and put their names in a hat or bag to randomly select one child. If there is no child aged less than 5 years go to section 3.

27. Child's name ....[________________________________]
28. Mother's name ....[________________________________]
29. Father's name..[________________________________]

30. Child's sex (M/F) ....[__]

31. Child's date of birth (dd-mm-yy).. [__|__]-[__|__]-[__|__]

32. Does the child sleep with the mother (Y/N)...[__]

33. Does the child sleep on 1. A bed with a mattress; 2. A bed without a mattress; 3. On a mattress or mat on the floor..[__]

34. Does the child <u>usually</u> sleep under a bed net (Y/N)...[__]
If yes, Did the child sleep under a bed net last night (Y/N)......................................[__]

35. From whom was the bed net purchased/obtained . [________________________][__]
36. How much did the net cost – if free indicate 0000 (KES) .... [__|__|__|__]
37. Has the net ever been treated with dawa (Y/N/D) ....[__]
If yes, was the net treated in the last 6 months (Y/N)...[__]
If yes, where and who treated the net... [________________________][__|__]
How much was paid for the net treatment – if free indicate 000 (KES)..............[__|__|__]

38. Does the child sleep in a room where the walls have been sprayed with insecticide within the last 12 months (Y/N)..[__]

39. Has the child had a **fever or hot body** in the last **14 days** (Y/N)................................[__]

If No go to section 3.

40. For how many days was/has the child been unwell ....[__|__]

41. Is the child suffering from a **fever or hot body TODAY** (Y/N).................................[__]

District-Enumeration-Household number –[__]-[__|__|__]-[__|__|__]

42. Has the child received any treatment for this fever (Y/N)....................................[__]

If yes, complete the following treatment history as per your training and manual

Order drugs	Day of illness	Where treatment sought (Codes-name of treatment source-Codes)	Anti-malarials or anti-pyretics (Codes & # tabs/spoons)	Money Spent on (Total KES)
1.				
2.				
3.				
4.				
5.				
6.				
7.				
8.				
9.				

43. What has been the total amount spent on drugs to treat this febrile episode (KES)...... .... [__|__|__|__]
44. What has been the total amount spent on transport during the treatment of this febrile episode (KES)[__|__|__|__]
45. What has been the total amount spent on consultation fees to treat this febrile episode (KES).... [__|__|__|__]

Appendix 4: Copies and lists of papers resulting from or related to the thesis

4.1 Amin, A.A., Marsh, V., **Noor, A.M.**, Ochola, S.A., Snow, R.W. (2003). The use of formal and informal curative services in the management of paediatric fever in four districts in Kenya. *Tropical Medicine & International Health*, **8**: 1143-1152.

4.2 Guyatt, H.L., **Noor, A.M.**, Ochola, S.A., & Snow, R.W. (2004). Use of intermittent presumptive treatment and insecticide treated bed nets by pregnant women in four Kenyan districts. *Tropical Medicine & International Health*, **9**: 255-261.

4.3 Hay, S.I., **Noor, A.M.**, Nelson, A., Tatem, A.J. (2005). Demography for epidemiology: the precision of large-area human population maps. *Tropical Medicine & International Health*. Submitted.

4.4 Tatem, A.J., **Noor, A.M.**, Hay, S.I. (2004). Defining approaches to settlement mapping for public health management in Kenya using medium spatial resolution satellite imagery. *Remote Sensing of Environment*, **93**: 42-52.

4.5 Tatem, A.J., **Noor, A.M.**, Hay, S.I. (2005). Accuracy of urban area delineation in Kenya. *Remote Sensing of Environment*, **96**: 87-97.

APPENDIX . NOT COPIED

ON INSTRUCTION FROM

UNIVERSITY